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ENHANCING LETHALITY THROUGH MARKSMANSHIP TRAINING MODERNIZATION

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ENHANCING LETHALITY THROUGH MARKSMANSHIP TRAINING MODERNIZATION

by

Robert J. Jankowski

June 2020

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ENHANCING LETHALITY THROUGH MARKSMANSHIP TRAINING MODERNIZATION

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Submitted in partial fulfillment of the
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ABSTRACT

Every Marine is a rifleman. However, the Marine Corps has failed to leverage technology to improve the art and science of marksmanship training, which has gone unchanged for almost 100 years. Marines score paper targets with pen and paper, wasting valuable time. The data collected is insufficient to precisely measure shooter abilities or evaluate analytically. The result is a lack of infrastructure and programs to leverage data analytics, machine learning, and artificial intelligence to aid in coaching Marines. This thesis expands on a previous Naval Postgraduate School thesis by continuing the development of tools to exploit digital marksmanship data to gain meaningful insights. With these tools, Marines would have unparalleled access to their historical shooting data and coaching feedback. Quantifiable measures will be used to provide coaching recommendations to improve rifle employment by providing more focused and effective training. We identify a more accurate method for calculating a probability of hit from observed data, which will allow the Marine Corps to measure lethality more accurately. We also offer recommendations for resource allocation to training facilities for marksmanship modernization and for programmatic requirements for automated data collection, storage, and use in analysis. By harnessing analytics and artificial intelligence, the Marines will more efficiently and effectively train Marines to be riflemen and enhance the lethality of the USMC.

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LIST OF ACRONYMS AND ABBREVIATIONS

AAAM	Association for the Advancement of Automotive Medicine
AI	artificial intelligence
AIS	abbreviated injury scale
CELIM	Center for Excellence in Lethality in Marksmanship
CFT	combat fitness test
CHRC	Carlos Hathcock Range Complex
CPG	Commandant’s Planning Guidance
EDIPI	electronic data interchange personal identifier
IPA	impact pattern analysis
KD	known distance
KDAS	known distance automated scoring systems
LOMAH	location of miss and hit
MCAS	Marine Corps Air Station
MCDP	Marine Corps Doctrinal Publication
MCOTEA	Marine Corps Operational Test and Evaluation Activity
MCRP	Marine Corps Reference Publication
mm	millimeter
ML	machine learning
NPS	Naval Postgraduate School
OAD	Operations Analysis Division
PFT	physical fitness test
P_{HIT}	probability of hit
P_{LH}	probability of lethal hit
PPE	personal protective equipment
USMC	United States Marine Corps
WTB	Weapons Training Battalion

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EXECUTIVE SUMMARY

Modernizing training and leveraging data analysis, machine learning, and artificial intelligence to unleash the potential of the individual Marine are key efforts tasked to the Marine Corps in the 38th Commandant of the Marine Corps' Planning Guidance (Berger 2019). This thesis explores the use of data science to modernize marksmanship training. We build on recent analysis by Captain Benjamin McCaleb (2018) at Operations Analysis Division in *The Marine Corps Rifle Marksmanship Lethality Capabilities-Based Assessment* which quantified lethality. We also leverage the work by Major Kevin Wheeler (2019) in his recently completed Naval Postgraduate School thesis, *Analytics to Enhance Lethality In Marksmanship,* in which he describes how a new system records the coordinates of the impacts of each round fired on the rifle range and designs performance metrics for quantifying accuracy and precision.

In this thesis, we continue these analytical efforts surrounding the measurement of the performance of Marines conducting marksmanship training. Specifically, we seek to explore the benefits of employing an automated scoring system and leveraging the data collected to make more informed decisions about individual shooter performance and improving the effectiveness of marksmanship training. We demonstrate some of the insights that can be gained by analyzing the data collected from automated scoring ranges.

We conduct round impact pattern analysis on marksmanship data consisting of over 330,000 shots taken at the Carlos Hathcock Range Complex located on Marine Corps Air Station Miramar. We display and analyze the distributions of the standard deviations and mean impact point as well as the accuracy and precision metrics proposed in Wheeler (2019) to provide insight on performance during different events, firing at different distances to the target, and from different shooting positions.

We demonstrate the usefulness of data collected during routine training to conduct an analysis like the research conducted by McCaleb (2018). This demonstrates the ability for consistent analysis on routine marksmanship training, rather than waiting for a deliberate study to be conducted and analyzed. We examine the assumptions used in previous studies and developed a more accurate method for approximating a probability of hit by taking bootstrapped samples of observed data as opposed to modeling based on a normal distribution.

The method proposed in this thesis is accurate to within 1% for every event when compared to the actual number of hits in the same area of the target. When duplicating the method employed in the McCaleb (2018), we found an underestimation of up to 10% when calculating the probability of hit. The figure below shows the comparisons between the observed, bootstrapped, and simulated hit probabilities. Our proposed method can be used to make better-informed decisions about training, equipment, and the performance of Marines under varying conditions from routine marksmanship training data.

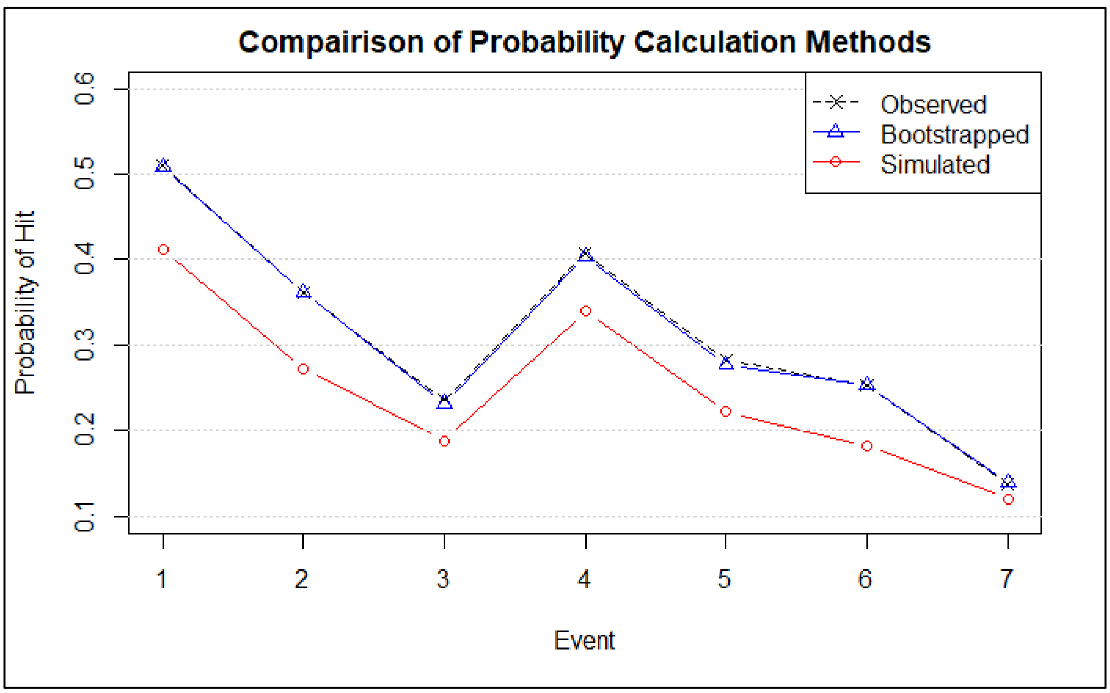

Figure 1. Comparison of Observed, Bootstrapped, and Simulated Hit Probabilities

We continue the development of the digital data book and incorporate statistical tests to identify patterns in individual shooter performance and use the results of these tests to provide feedback to the shooter and their marksmanship coach. These tests provide statistical backing to confirm what we may or may not see with our eye. We present a method to quantify the improvements that can be expected with training time by comparing the performance of the same group of Marines over three training days. With more automated systems and the collection of data over time, this may prove to be a truly valuable way to make programmatic decisions regarding the Marine Corps Marksmanship program and focus spending both in terms of time and money.

We look at the increased insights that can be gained by considering impact pattern analysis and statistical modeling compared with the current point value scoring techniques. We identify substantial variability in standard deviations, accuracy, and precision measurements when examining 143 examples of shooters who scored the same point value on an event. These differences can be used to discern specific deficiencies and allow for additional metrics to be employed in evaluations.

The ability of Marines to lethally employ service rifles is critical to success on the battlefield. The Marine Corps must develop new methods to modernize marksmanship training and evaluation to improve the lethality of the individual Marine. This thesis demonstrates the capabilities of employing statistical machine learning and artificial intelligence to provide valuable information for making decisions which can lead to better decisions, more lethal Marines, and a greater probability of success on the battlefield.

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Berger DH (2019) *38th Commandant's Planning Guidance 2019.* Washington, DC, https://www.hqmc.marines.mil/Portals/142/Docs/%2038th%20Commandant%27s%20Planning%20Guidance_2019.pdf?ver=2019-07-16-200152-700.

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I. INTRODUCTION

> Ultimately, the purpose of the Marine Corps rifle marksmanship program is to provide Marines with the ability and confidence to deliver lethal rifle fire under combat conditions.
>
> — McCaleb, 2018

A. PROBLEM STATEMENT

The Marine Corps does not currently have a formal plan to implement data analytics, statistical machine learning (ML), artificial intelligence (AI), automated scoring, or automated administrative reporting on Marine Corps marksmanship training. The current range data collection Corps-wide is insufficient in scope and detail to be able to use in data analytics or machine learning. However, one instance of an automated range exists and provides an opportunity to act as a proof of concept demonstrating how data analytics could be used to enhance marksmanship training. Luckily, at this time, the Corps is pursuing a range renovation program that makes this study timely and informative to that effort.

Marksmanship training currently involves recording round impact data by hand on paper, which is administratively burdensome, and prone to human error. Coaching and feedback are based on this manually collected data, which is the burden of the shooter on the line, with a subjective component, and on shooters who must man the targets in the "pits."

At the end of the training evolution, only the overall score is recorded. However, the total score by itself does not capture enough information for shooters to identify areas for improvement over the years, let alone to enable the training of machine learning algorithms to provide any feedback to shooters or coaches. One marksmanship range in the Marine Corps, the Carlos Hathcock Range Complex (CHRC) located on Marine Corps Air Station (MCAS) Miramar, CA, collects and scores shot coordinate data, but until the recent thesis effort from Kevin Wheeler (2019), no analysis had been conducted on the data since it was installed in 2006. His thesis focused on visualizing the data and identifying a lethality metric as a data-informed measurement of accuracy and precision as an improvement on the ring based five-point scoring method currently used.

The next section provides information about the Marine Corps marksmanship training program, and the systems used to collect the data for this thesis to provide the unfamiliar reader details on the specifics of the training conducted. It also provides details about the range where the case study data was obtained.

B. MARINE CORPS MARKSMANSHIP

> All Marines share a common warfighting belief: Every Marine a rifleman. This simple credo reinforces the belief that all Marines are forged from a common experience, share a common set of values, and are trained as members of an expeditionary force in readiness.
>
> —USMC, 2016

This section provides background on the Marine Corps marksmanship program, and details the Table 1A, Known Distance (KD) course of fire, including descriptions of the targets and shooting positions used. This section also provides a description of the training range and the electronic scoring system, which generates the data used in the analysis for this thesis.

1. Marksmanship Fundamentals

MCRP 8–10B.2 *Rifle Marksmanship* (USMC, 2016) is the Marine Corps publication that details the methods for instructing and executing all elements of the Marine Corps Marksmanship program. In the Marine Corps, all Marines receive the same initial rifle training, learning the same fundamentals regardless of their Military Occupational Specialty (MOS) specialty. The initial rifle training and evaluation are officially titled Table 1A, referred to collectively as the fundamental rifle marksmanship firing tables. We include this information here, as it is the same course of fire completed in the data set we examine in this thesis. Figure 1 shows Marines participating in marksmanship training.

Figure 1. Marines Shooting at CHRC, MCAS Miramar, CA
Source: Wheeler (2019)

2. Table 1A Rifle Qualification

The intent of the training and initial qualification is to ensure that the Marine has gained the required knowledge and skills to employ the service rifle safely, effectively, and accurately. Table 1A includes firing the service rifle from four firing positions including the standing, kneeling, sitting, and prone positions. The distance between the Marine and the target varies between 200 and 500 yards. The time available for each round to be fired varies from approximately one minute to approximately 6 seconds, depending on the event. Cumulatively, Table 1A is designed to refine and evaluate the Marines' ability to perform the fundamentals of marksmanship (USMC, 2016). Figure 2 shows the course of fire in Table 1A, detailed in the *NAVMC 11660*, *Annual Rifle Training Databook* (Weapons Training Battalion [WTB], 2019) the results of which will be examined in the next section.

TABLE 1A COURSE OF FIRE

BLOCK / DAY	STAGE		RANGE	TIME	AMMO	FILL PLAN # MAGS / # RNDS EA.	TARGET	POSITION	SLING
1 & 2	1	SLOW-FIRE	200	25 MIN	20	4/5	ABLE	SITTING KNEELING STANDING ANY	LOOP LOOP PARADE
	2	RAPID-FIRE	200	60 SEC 60 SEC	20	2/10	DOG	SITTING	LOOP
	3	SLOW-FIRE	300	5 MIN	5	1/5	ABLE	SITTING	LOOP
	4	RAPID-FIRE	300	60 SEC 60 SEC	20	2/10	DOG	STANDING TO PRONE	LOOP
	5	SLOW-FIRE	500	15 MIN	15	1/10	B-MOD.	PRONE	LOOP
3	1	SLOW-FIRE	200	20 MIN	15	3/5	ABLE	SITTING KNEELING STANDING	LOOP LOOP PARADE
	2	RAPID-FIRE	200	60 SEC	10	1/10	DOG	SITTING	LOOP
	3	SLOW-FIRE	300	5 MIN	5	1/5	ABLE	SITTING	LOOP
	4	RAPID-FIRE	300	60 SEC	10	1/10	DOG	STANDING TO PRONE	LOOP
	5	SLOW-FIRE	500	10 MIN	10	1/10	B-MOD.	PRONE	LOOP

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Figure 2. Course of Fire Table 1A Data Book Excerpt. Source: WTB (2019).

Throughout the course of fire, Marines fire at different targets, depending on the event they are participating in. The three target types are named the Able, Dog, and B-Modified. Each target has different areas that correspond to the point value of a round that impacts that area. The black shaded areas are worth the most points, at 5 points per round. Moving out from the center, rounds are scored at 4, and 3 points each ending with 2 points for a round that strikes the paper outside of the marked target area. Rounds that fail to impact the paper receive no points. Figure 3 shows the dimensions and shape for each target type used in the Table 1A training.

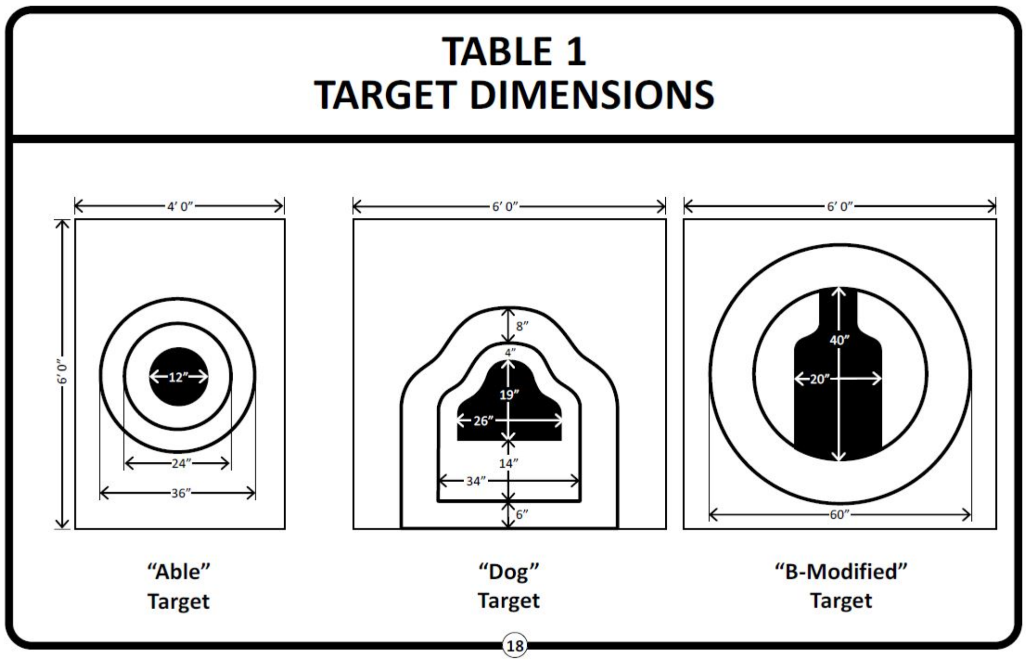


Figure 3. Target Dimensions. Source: WTB (2019).

3. Location of Miss and Hit Technology

Location of Miss and Hit (LOMAH) is the name of the technology used to pinpoint the location of the round as it passes through the target.

> When the technology is employed on a rifle range in a stationary capacity, industry identifies these systems as Known Distance Automated Scoring Systems (KDAS). LOMAH systems exist in many different forms. The Marine Corps has one KDAS range in operation at Marine Corps Air Station (MCAS) Miramar at the Carlos Hathcock Range Complex (CHRC) in San Diego, CA. (Wheeler 2019, p. 18).

At the CHRC, Marines remain stationary on the firing line, and fire at targets that automatically present at 200, 300, and 500 yards away. This configuration is the reverse from most KD ranges in the Marine Corps, where targets are located in one location and are manually scored by Marines waiting for their turn to fire. The shooters fire at one set of targets and move from yard-line to yard-line in-between events, starting at the 200 yard-line and moving back to the 500 yard-line. A diagram of the CHRC configuration is provided in Figure 4.

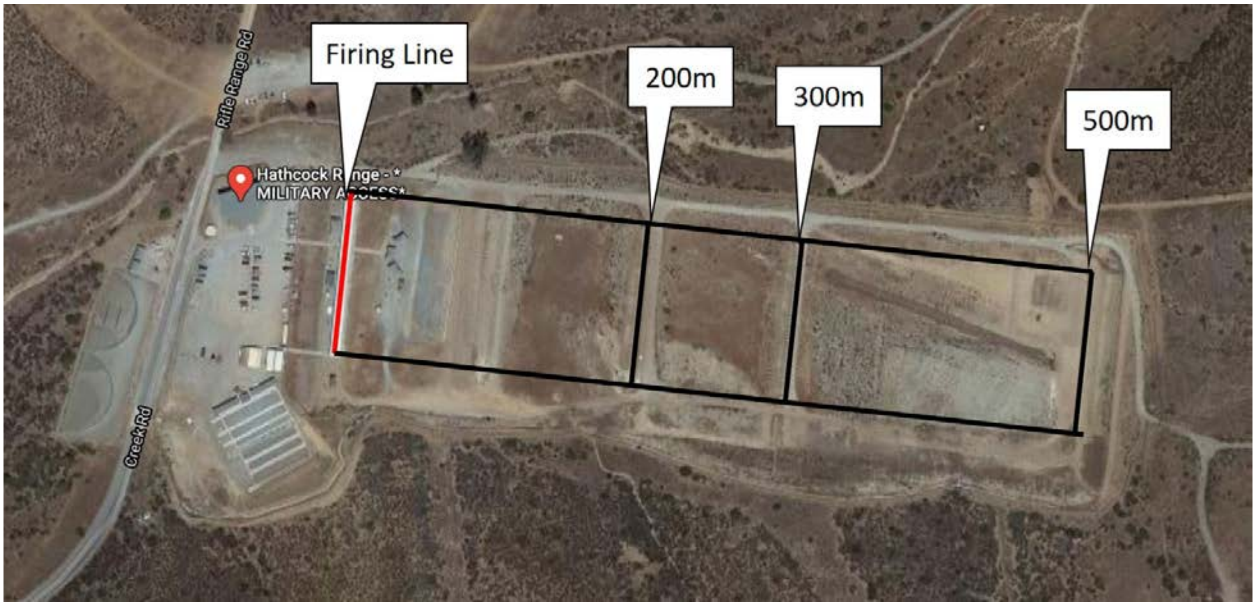
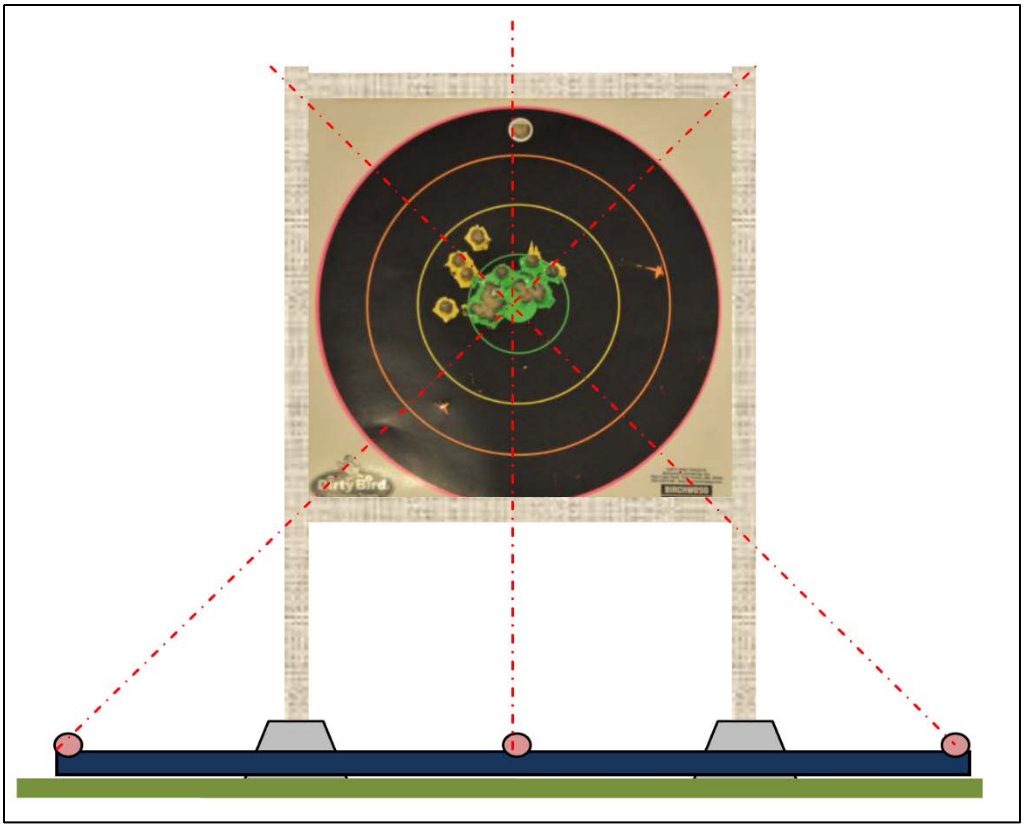


Figure 4. Overhead Image of the CHRC at MCAS Miramar, CA. Adapted from Google Maps (2020).

The LOMAH system uses sensors located on the firing line and at the target points to locate the round as it passes through the target. The sensors use the soundwave of the round to locate the precise location on the target face. "Depending on the distance of the round to the various microphones, the system can triangulate the exact position of the round, down to a calibrated 3 mm" (Wheeler 2019, p 16). The sensor on the firing line is used to activate the sensors on the target face to ensure that the round is annotated for the correct lane. Figure 5 depicts a diagram of the sensors at the target face triangulating the location of the round.



Sensors triangulate the location of the round as it passes through the target.

Figure 5. Triangulation of Round Impact. Adapted from Davey (2019).

According to Wheeler (2019, p. 17), "This process provides a precise X-Y coordinate, with reference to a vertical cartesian plane. Software then calculates the location of the impact site on the target and determines the score value of that shot, providing feedback to the range operator and shooter with respect to shot placement and scoring." This information is currently used in two ways. First, the information is passed to a screen at the target point, which provides accurate and immediate feedback to the shooter. An image of the screen is included in Figure 6.

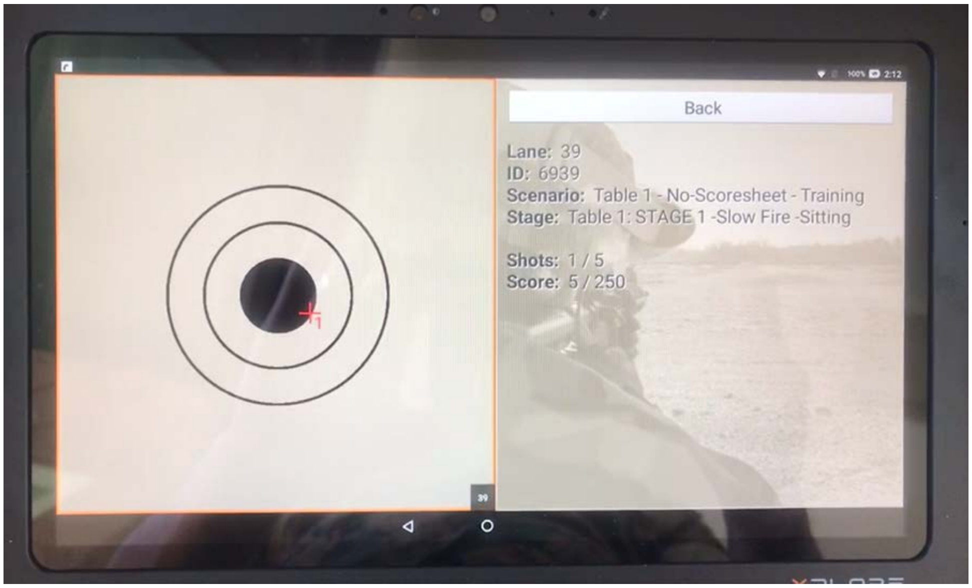


Figure 6. Graphical User Interface Display. Source: Wheeler (2019).

Simultaneously the information generated by the sensors is transmitted to the central computer system used to operate the range. At the central computer terminal, the point value of each round is saved in a scoresheet, and a .pdf document is generated for each shooter to record their qualification score. Currently, the coordinate data is not saved or exported; however, this was recommended by Wheeler 2019.

C. THESIS OBJECTIVE

The goal of this thesis is to demonstrate the capabilities of data analysis and ML techniques to quantify shooter performance, to calculate benchmarks for performance improvements in marksmanship training assessments, and to outline the requirements and processes required to implement AI-enhanced marksmanship coaching.

In order to employ AI and ML to improve the coaching the Marine Corps provides to shooters, the Corps will need to establish a framework. One conceptual method for establishing this framework was described by Cassie Kozyrkov, the head of Decision Intelligence for Google, in a 2019 article titled *12 Steps to Applied AI, A Roadmap for Every Machine Learning Project* (Kozyrkov, 2019).

The steps are as follows:

1. Define your Objectives

2. Get access to data

3. Split your data

4. Explore your data

5. Prepare your tools

6. Use your tools to train some models

7. Debug, analyze, and tune

8. Validate your models

9. Test your model

10. Productionize your system

11. Run live experiments to launch safely

12. Monitor and maintain… forever (Kozyrkov, 2019)

In this thesis, we will explore the first six steps, and we will provide recommendations for the implementation of a functioning system. We intend to establish the framework required for the use of machine learning techniques to provide shooter and coach feedback, which will be required as a foundation to be able to provide data and ML-enabled coaching feedback to Marines. The goal will be to assist in the requirements generation process to fund the infrastructure required for this training modernization.

In support of these goals, we will employ the metrics developed in previous work, as a method of classifying the impact patterns, and develop descriptive statistics about the impact data. We will demonstrate the usefulness of the analysis by providing example feedback to the shooters and coaches with the intent of improving marksmanship performance.

D. LIMITATIONS

1. One Range

As noted in Wheeler (2019), the data for this study comes from a single range complex. While this has some benefits in the initial modeling, it has limitations for the generalization of the results across the Marine Corps. There will be biases in the data caused by the physical layout of the range, the prevailing wind conditions at the range, and the weather at the range. The population of Marines who are stationed at MCAS Miramar, and who train on the CHRC, will also introduce bias into the sample to the extent they differ from the Marines as a whole. This limitation is addressed in the recommendations section of Chapter V.

2. One Course of Fire

This thesis focuses on Table 1A, the static position, known distance portion of the rifle range. This course of fire was designed to refine and measure the fundamentals of Marksmanship. Marines will shoot from 200, 300, and 500 yards, and fire from the sitting, kneeling, standing, and prone position. Training consists of three days: two days of practice with 80 rounds fired to refine skills, and a qualification day with 50 rounds fired to measure the performance achieved.

3. Identifying Data

All Marines in this analysis are treated as equal; there is no identifying data to distinguish shooters, other than the range detail, target point, and relay they trained on. An analysis including background information and performance on other evaluations such as Physical Fitness Test (PFT), Combat Fitness Test (CFT), previous rifle marksmanship performance, and cognitive tests are recommended in Chapter V.

4. Weapon Type

The weapon type was not captured in the data and therefore was not included in the analysis. The weapon is responsible for a portion of the variability in the impacts and, if that data was available, it would allow for greater accuracy in the analysis. A recommendation to address this limitation will be covered in Chapter V.

5. Weather Data

Weather conditions, especially wind has a significant impact on a round in flight, and therefore on a Marine's ability to shoot accurately. We were not able to get detailed weather data to correlate with the dates of recoded training data. A recommendation for including weather data in data collection efforts and future work is included in Chapter V.

E. ASSUMPTIONS

1. Process of analysis can be generalized.

Similar analysis can be conducted using LOMAH data on the different courses of fire, and additional insights can be gained, such as the effects of moving, and the effects of wearing Personal Protective Equipment (PPE). The work conducted in this thesis is intended to be a demonstration of capabilities and is designed to be flexible enough to employ on any course of fire. We include recommendations for how this analysis can be repeated in Chapter V.

2. Shooters are a representative sample of Marines.

This assumption is being made for the sake of the conduct of this analysis only. It is not a realistic assumption for many reasons, including those listed in the limitations section. In order for the specific metrics calculated in this thesis to be used in future decision making, the analysis conducted here must be repeated on a broader set of Marines. Therefore, the calculations conducted here are intended to be a representation of what is possible, if the appropriate data management procedures are put in place.

Additionally, McCaleb notes that it is important to assume that the "Marines firing Service rifles during data collection were familiar with applicable Marine Corps doctrine; ranges, facilities, and targets; weapons and equipment systems; training" (2018, p. 4). This assumption is important because the intent is to measure Marines to determine a baseline of performance. This baseline will allow for follow on research to identify the effect of other conditions.

3. Shooters stay on the same target point and relay for the whole detail.

There is some risk associated with this assumption; there is a possibility Marines moved from one target point or relay for personal schedule reasons, or due to equipment malfunctions. However, this assumption needs to be made to connect one day of data to another in the data set. We will address data collection along with recommendations for future work to verify with all shooter data and history in Chapter V.

4. Ranges can be equipped with LOMAH sensors.

The data used for all of the analysis in this thesis is derived from automated LOMAH sensors to capture the location of the impact of the rounds fired on the target. All the calculations and feedback are derived from this data, and therefore the sensors will be required to be installed on Marine Corps marksmanship training ranges for the results of this thesis to be implemented Marine Corps wide. Installation and employment of these sensors have been recommended by McCaleb (2018) and by Wheeler (2019), and more detail on this is provided in Chapter II. Our recommendation for the implementation of LOMAH sensors into all marksmanship training ranges is included in Chapter V.

F. THESIS ORGANIZATION

Chapter II provides an in-depth review of previous studies on marksmanship training, the collection and utilization of marksmanship data, and concepts for employing machine learning techniques to modernize training. In Chapter II we also provide motivation and justification for the research conducted in this thesis by referencing recent Marine Corps guidance.

Chapter III describes the data used for this study by putting it in the context of the range it was collected on and the details of the training conducted. It begins by discussing the data as it was obtained and describes the methods and tools used to clean, format, and structure the data. We describe the methods and mechanics of the data analysis required for this study collectively referred to as Impact Pattern Analysis (IPA). We analyze the aggregate data and identify trends in overall performance. We report on identified trends from the data with insights gained from the analysis of the data. We finish chapter III by checking the normality assumptions used in a previous study. We proposed a method for calculating a hit probability by sampling observed data, which we find is more accurate than calculations using data simulated using the normal distribution.

Chapter IV provides a case study in the use of data analysis, and statistical analysis techniques to demonstrate the value of the detailed coordinate shot data with the focus on an individual shooter. We use data analysis to identify and quantify performance metrics, and compare the shooter to all shooters as a whole. We describe the data book in the context of Marine Corps marksmanship and detail the transformation of the raw impact data into a digital data book. This chapter explores the possibilities for the employment of data analysis at the individual Marine level to demonstrate insights and trends across the training event and provide more effective feedback to the shooter. The purpose of the digital data book is to demonstrate the capabilities of analysis and to inform requirements generation.

Chapter V includes the conclusion of the thesis effort and discusses the results of the study, as well as the applications. We provide recommendations for electronic scoring on marksmanship training ranges and a recommendation for the implementation of the AI coaching tools. Recommendations for follow on work which will be useful to fully implement the tools discussed are also provided. We provide insights and recommendations for data collection, analysis, and requirements for machine learning-enabled marksmanship feedback and/or coaching. Finally, we make recommendations for requirements development for KDAS, and LOMAH systems to export data in a format which can be used for live feedback and storable results, including centralized data storage and analysis.

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II. LITERATURE REVIEW

This chapter reviews the research and guidance used as a foundation and guide for this thesis. The first section covers Marine Corps guidance relating to training modernization, training theory, and marksmanship. In the second section, we review recent research conducted specifically in the area of analytics and marksmanship. Throughout the chapter, we tie in the source documents to the research conducted in this thesis, both as a foundation and as a frame of reference for common language and purpose.

A. MARINE CORPS GUIDANCE

> We do not currently collect the data we need systematically, we lack the processes and technology to make sense of the data we do collect, and we do not leverage the data we have to identify the decision space in manning, training, and equipping the force.
>
> —General David H. Berger, USMC, 2019

Automated data collection, data analysis, and AI-enabled marksmanship coaching should be a top priority to the Marine Corps. This section details recent guidance published by the commandant of the Marine Corps and his specific guidance applicable to the research conducted in this thesis. The second section details the most recently published *Marine Corps Doctrinal Publication 7, Learning*. In this new publication, the Marine Corps lays out its theories on learning, training, and coaching.

1. Commandant's Planning Guidance

In the 38th Commandant's Planning Guidance (CPG) published in 2019, the Commandant calls for the use of data science to improve education and training as one of five focus areas for the Marine Corps. Specifically, on training, General Berger writes that "The Marine Corps can no longer accept the inefficiencies inherent in antiquated legacy systems that put an unnecessary burden on the warfighters" (2019, p. 14). This thesis seeks to demonstrate a process to improve training by providing a path leveraging technology to efficiently collect shooter data, make sense of it, and provide insights. These insights can enable the Corps to leverage the data to improve individual capability, enhance training, use resources appropriately, and ultimately modernize marksmanship training enhancing the lethality of the Marine Corps.

The commandant focuses the goal for the employment of data science techniques: “All of our investments in data science, machine learning, and artificial intelligence are designed to unleash the incredible talent of the individual Marine” (Berger 2019, p. 15). This thesis effort will aid the training transformation through the demonstration of data science capabilities to shape the marksmanship talents of Marines, as well as making recommendations on the training structure and range infrastructure requirements to employ these capabilities.

The Commandant specifically calls for upgraded training facilities to modernize and leverage technology: “Moreover, our training facilities and ranges are antiquated, and the force lacks the necessary modern simulators to sustain training readiness.…. Modernizing our force structure requires a deliberate review of our installations and a deliberate plan to invest, divest, and reset” (Berger 2019, p. 6). We seek to quantify the benefits which will be gained by the investment in technology for these specific ranges through the value of the analysis it enables, resulting in insights and training improvement. Our goal is to influence the way the Marine Corps invests in automated ranges, data management procedures, and the employment of AI- enabled feedback tools—all of which will enhance the tools available to train Marines.

The Commandant goes on to describe the paradigm shift required to transform our training model. “We must change the Training and Education Continuum from an industrial age model, to an information age model…But first, we must codify what is meant by an information age model of training and educating Marines” (Berger 2019, p. 13). In an industrial age model, all Marines are treated the same and given the same resources and practice time. An “information age” model would be able to identify which Marines will benefit most from additional training and resources and identify what each Marine needs to improve to enhance their individual proficiency. Finally, the commandant has directed that funding be prioritized in support of the training transformation (Berger 2019, p. 13).

This thesis will provide recommendations on the prioritization of this funding to outfit Marine Corps live fire ranges.

The Commandant goes on to call for the establishment of enduring programs and procedures for the employment of technology to modernize the way the Marines train and provide feedback to its shooters. “Where we have individual leaders and organizations that are trying to adopt the best practices in data science and data analytics, it is often accomplished through the heroic efforts of a few individuals rather than the organized and sustained effort required to transform how we sense, make sense, and act” (Berger 2019, p. 14). While we will provide a path here in this research, it will take additional research and the establishment of programs of record to properly collect, manage, and gain the full value of these insights and to implement these new technologies.

2. Marine Corps Doctrinal Publication (MCDP) 7 Learning

The publication of MCDP 7 “Learning” is part of a broader focus to meet the Commandant’s intent of advancing the state of training and education for the Marine Corps by formally defining the principles associated with effective learning and teaching (United States Marine Corps [USMC], 2020). The principles outlined in MCDP 7 will guide the development of the tools we will develop here to enhance marksmanship training. “Training prepares Marines to deal with the known factors of war (e.g., the importance of good marksmanship)” (USMC, 7 2020, p. 1–4). It goes on to describe that “Learning is developing knowledge, skills, and attitudes through study, experience, or instruction. It is a never-ending progression that includes understanding *why* something is important—the intent of learning” (USMC, 2020, p. 1–4). We expect that by visually displaying the relevant aspects of a Marine’s performance, it will help him or her to better understand each of the fundamental components of Marksmanship, and his or her progression in their own skills.

MCDP 7 lays out five learning principles for Marines, which describe the mindset required for effective learning, and outlines the responsibilities for both the Marine who is learning, as well as those who are involved in the learning: instructors, teachers and those involved in structuring and developing training programs. The learning principles are

1. Know yourself and seek self-improvement.
2. Be ready and willing to learn.
3. Understand why you are learning.
4. Provide and receive constructive feedback.
5. Learning is purpose-driven to develop professional competence.

(USMC, 2020, p. 1–9)

a. Supporting Shooter and Coach

In this thesis, we will develop tools and technology focused on learning principles number four and five, by providing useful feedback on shooter performance with two core audiences in mind. First, we will focus on the shooter, and identify trends in his or her performance, with the goal of providing insights and feedback which are not readily apparent or accurate when viewing in a traditional databook or using traditional scoring tools. This information will enable the Marine in pursuing principle one, knowing their marksmanship skills, and seeking to improve in the areas which will have the most impact on their lethality.

The other use for the tools we seek to develop is the marksmanship coach and the instructors who are working to train Marines in marksmanship and lethality. These tools will aid our coaches in providing evidence-based feedback to shooters to identify trends that are affecting their lethality. Coaches with multiple shooters firing cannot pay attention to all shooters simultaneously. The proposed methods of collecting and displaying shot data will enable the coaches to view and digest information that they would otherwise have missed, to ensure their assigned shooters are progressing, and ensure they are focusing on the areas needed most. MCDP 7 goes on to say: "Regardless of location or position, Marine instructors are knowledgeable, skilled, competent, and confident in their abilities. They know their Marines' strengths and weaknesses and empathize with the learners' challenges to better understand how they can tailor the learning environment to be more effective" (USMC, 2020, p. 3–16). The tools developed in this thesis will assist the coaches in understanding their student's skills, strengths, and weaknesses, ultimately enabling them to be more effective coaches.

"Marines leverage the art and science of learning along with helpful technologies to enhance learning environments, tailor learning experiences, and provide constructive feedback to accelerate learning" (USMC, 2020, p. 3–19). There is currently no method for accomplishing this during marksmanship training. Developing tools and visualizations based on automated data collection will enhance marksmanship training. "Marines continuously assess and adapt the Marine Corps' learning content, methods, exercises, and environments to ensure that they are relevant and effective" (USMC, 2020, p. 3–19). Once these tools are in place, a process can be enacted to determine which tools are the most useful and expand and refine tools to other courses of fire and weapon systems. "Technology can support, expand, and individualize learning; it is one of many tools to support learning objectives. Some technologies also collect data on learner performance to enhance feedback and after-action reviews. Technology can facilitate individual and collective skill development, feedback on current performance, and supplemental instruction tailored to individual or unit needs" (USMC, 2020, p. 3–18).

Effective training is learner-centric. The current method for marksmanship training is the epitome of industrial-age training. Marines are organized into groups and run through scripted training sessions designed to maximize safety, throughput, and range utilization. These processes were created for the sake of efficiency and safety; however, there are limitations in that all Marines are treated identically, which does not match the way that Marines learn.

> Science has also identified that individuals and teams have differences in the way they learn, with varying sensory preferences for learning, competencies, and strengths. These differences are essential components of the learning process and can be useful knowledge for structuring or engaging in learning events so that learning is more effective. (USMC, 2020, p. 1–15)

We can leverage data analysis and machine learning to divide shooters into groups based on competency and build the training around what those Marines need to succeed. LOMAH sensors will enable a learner-centric model based on data and analysis, as opposed to the current industrial age model based on analog pen and paper recording. "The learner-centric model tailors the learning delivery methods to be most effective for the learners, rather than defaulting to a 'one-size-fits-all' instructional approach. … Marines will be more engaged and enthusiastic about learning when the methods are adjusted for their aptitudes" (USMC, 2020, p. 3–11). The tools developed in this thesis will enable a Marine and their marksmanship coaches to work together to reinforce the shooter's inherent strengths, and work to overcome the weaknesses, ultimately making the individual Marine more lethal.

Data analytics, applied at the individual shooter level, can provide unparalleled feedback to a shooter who is learning new skills. This supports the fourth learning principle, "***to provide and receive constructive feedback***. One cannot learn without feedback" (USMC, 2020, p. 2–8) (emphasis in the original). MCDP 7 conveniently uses the example of a Marine learning marksmanship as its example for intrinsic (internal) and extrinsic (external) feedback:

> A Marine's own perception that he or she jerked the trigger when shooting a rifle, then adjusting the trigger pull on the next shot, would be an example of using intrinsic feedback. In this same example, extrinsic feedback would be a marksmanship instructor identifying the error to the Marine, then demonstrating the proper trigger pull. (USMC, 2020, p. 2–8).

The data provided to the shooter is another layer of automated objective extrinsic feedback, which will be critical in developing the instincts required for refined intrinsic feedback.

b. Supporting Assessments through Data-Driven Feedback

"Assessments are employed to provide learners with constructive feedback so that they can further develop professionally, rather than an arbitrary test score that does not capture growth or change" (USMC, 2020, p. 3–17). Assessments are the tool used to drive the learning or training process. "Learning assessments facilitate and guide the learning process to determine whether the learner is proficient in required competencies" (USMC, 2020, p. 3–17). The tools we develop will both use the results from the already developed and implemented assessments in the Marksmanship training program, as well as provide more detailed insights than the results of the assessments alone demonstrate. Assessments "serve as feedback tools for both the instructor and the learner, assessing the learner's progress and the instructor's effectiveness" (USMC, 2020, p. 3–17).

In this thesis, we will be examining the first three assessments in the Marksmanship training continuum. Each training event is an assessment, and the purpose of each aligns well with the model described in MCDP 7 for the types of assessments: diagnostic, formative, and summative. The first event is the diagnostic assessment; the goal is to gauge the shooter's performance and identify what needs to be worked on. The second event is the formative assessment to "provide feedback to the instructor and the learner during the learning activity" (USMC, 2020, p. 3–17). Finally, the evaluation is the summative assessment which is used to "identify the learning that occurred after the learning activity has completed" (USMC, 2020, p. 3–17). The result of the summative assessment is the qualification score that is entered into the Marine's record. "The most effective instructors use the coach-teach-mentor approach to provide learners with constructive feedback" (USMC, 2020, p. 3–17). This method of phased assessments with opportunities for feedback from the coaches throughout the process will be aided by the feedback provided at the end of each assessment by the analysis in the digital data book.

"The most important factor in this philosophy is the importance of continuous learning throughout our careers for warfighting" (USMC, 2020, p. 2). Throughout this thesis, we will be analyzing a Marine's performance in a Marksmanship training and evaluation event. This is, however, just one event over the course of his or her time in service for the Marine Corps. There is currently no data collection method that can be used to identify trends in performance from one event to another, other than the total aggregate score. "The final principle is that learning is purpose-driven to develop professional competence. Learning has specific goals and measurable objectives to gauge progress toward developing competencies" (USMC, 2020, p. 1–12). A digital databook, as we describe it, will be greatly beneficial for comparing, tracking, and measuring performance from one event to another, without relying on memory or managing paper logs across a career. "Each Marine should identify professional learning goals, establish a plan of action, seek feedback, and regularly assess his or her progress" (USMC, 2020, p. 2–11). Enabling the digital data book for each Marine would provide the means to do this for each Marine's most basic and celebrated skillset: Rifleman.

“The Marine Corps’ organizational culture itself must continue to change and adapt to enable effective learning. This requires that the Marine Corps continuously explore new ideas, rigorously assess their feasibility and effectiveness, and implement ideas that work” (USMC, 2020, p. 2–13). This thesis is part of an effort to encourage the use of automated scoring by demonstrating the feasibility and effectiveness that these technologies, paired with machine learning and data analytics techniques, can have in training Marines to be more lethal with their small arms. The Marine Corps’s central warfighting philosophy is Maneuver Warfare, which is to employ our strengths against an enemy’s weakness to be as effective as possible. In this framework, strengths are referred to as surfaces and weaknesses as gaps. MCDP 7 uses this framework to explain the relationship between the learner, the instructor, and the learning process. “For the Marine learner, *surfaces* are areas of existing understanding—strongpoints that Marines maintain, build upon, and relate—while *gaps* are areas of weaknesses in knowledge, experience, or competencies—areas that the instructor and the learner need to fill with new understanding and practice” (USMC, 2020, p. 3–7). The tools developed in this thesis will enable the Marine and their coach to identify the relevant surfaces, and gaps, and work together to succeed. “The Marine Corps as an institution demonstrates a focus and commitment to encouraging career-long learning by continuously refining learning methods and providing resources and opportunities for professional development” (USMC, 2020, p. 2–10). This research is part of the Marine Corps’ commitment to refining the training process.

B. RECENT RELATED RESEARCH

1. Analytics to Enhance Lethality in Marksmanship

The first effort using automated range data was the thesis of Wheeler (2019) titled *Analytics to Enhance Lethality in Marksmanship*. This thesis imported marksmanship data from the LOMAH system from the CHRC located on MCAS Miramar, California. The work focused on cleaning, organizing, and visualizing that data and the development of a lethality metric based on the precision and accuracy of round placement calculated from the data. Wheeler briefed his research to the Commandant of the Marine Corps in March

2020, who indicated this is exactly what our Corps needs and insisted the efforts must continue.

Aside from the research completed by Wheeler (2019), there has been no other effort to bring together, analyze, or use the data collected on the CHRC. Additionally, there is no effort to provide an objective assessment of the value of updating USMC ranges to LOMAH ranges, leveraging the data, or how it can be used to increase Marine Corps lethality. Specific details of the accuracy, precision, and lethality calculations will be addressed in later chapters.

In addition to the analysis behind the development of analytic -based measurements of the distributions of round impacts, Wheeler created tools to transform the data extracted from the LOMAH system and display it visually on an image of the target face. These visualizations are the first major step toward creating a digital data book. Wheeler posited that this automated visualization of data will help coaches and shooters understand their abilities, identify discrepancies, and improve.

> If the data collection system and the application were available via an online server, this tool could potentially provide the information in perpetuity and enable a shooter to revisit his or her shooting strengths and weaknesses at the start of every range. In this sense, a 'digital data book' would be automatically maintained for each Marine, allowing for him or her to access the information at the start of each range training period and, working with a coach, build a strategy on what positions or course of fire to focus on for training time. (Wheeler, 2019 p. 34)

The visualizations and trends analyzed in *Analytics to Enhance Lethality in Marksmanship* were limited to one day of training and focused on the qualification day. A major effort of this thesis will be to continue the efforts to develop a digital data book, expand the analysis to three days of training, and identify and quantify the shooters' performance over the course of fire. "Focused at three levels, the individual Marine, the marksmanship coach, and the unit leader, the concepts presented here provide a means by which Marines can take otherwise unreadable data and translate it into actionable information" (Wheeler, 2019 p. xvi). Our goal is to focus specifically on tools to improve marksmanship training.

The remainder of *Analytics to Enhance Lethality in Marksmanship* was focused on the Marine Corps marksmanship structure and organization. Wheeler attended and briefed his results to the FY20 Combat Marksmanship Symposium. The recommendations outlined in his thesis are prerequisites for the work in this thesis to be employed. He recommends the employment of LOMHA systems on ranges across the Marine Corps and for the establishment of a Center for Excellence in Lethality in Marksmanship (CELIM). He argues that the establishment of one organization to enhance the science of marksmanship training and expertise will put CELIM in the best position to advocate for the Marine Corps. "By establishing CELIM, the Marine Corps creates a collection point for resident knowledge, lessons learned, and data which will greatly enhance the abilities of Generals in the Commandant's immediate staff to make choices on where to allocate resources toward advancing marksmanship in the Marine Corps" (Wheeler, 2019 p. xvi). The CELIM would be the central organization to remotely analyze data, and develop additional methods for employing the data. From this centralized position with access to the data, the Marine Corps can make the appropriate decisions on manning, training, and resource employment.

Wheeler's efforts and follow-on work will "help the U.S. Marine Corps empower Marines, at every level, to get the most out of their time spent on the rifle range, strengthening the idea of 'every Marine a rifleman'" (2019 p. xvi). This thesis will expand on and reinforce his work.

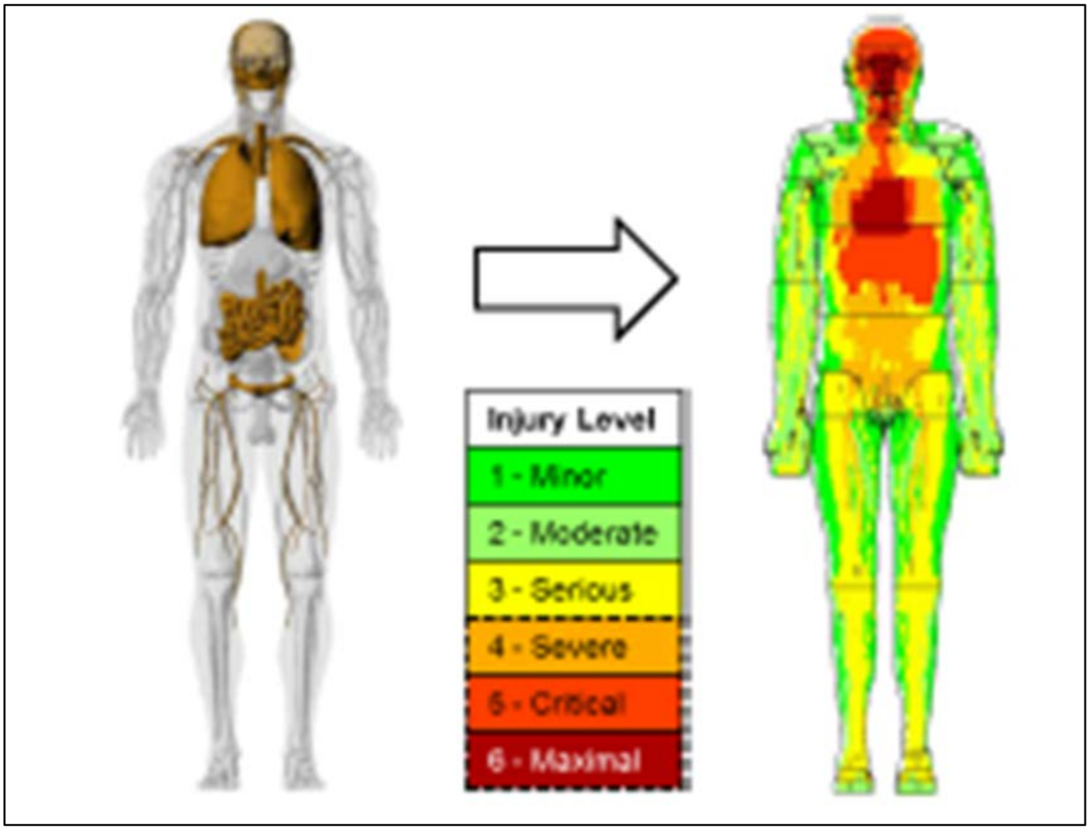
2. The Marine Corps Rifle Marksmanship Lethality Capabilities-Based Assessment

Operations Analysis Directorate (OAD), Marine Corps Combat Development Command (MCCDC), Headquarters Marine Corps completed a study titled *The Marine Corps Rifle Marksmanship Lethality Capabilities-Based Assessment* (*Lethality CBA*) in November 2018 (McCaleb 2018). The report identified gaps in capabilities associated with rifle marksmanship lethality and addressed those gaps by defining lethality as it relates to marksmanship, and how the lethality fits in with the defined operating concepts. The study was completed by conducting a functional area analysis, studying all aspects of rifle marksmanship; a functional needs analysis, analyzing the requirements; and a functional solutions analysis to recommend solutions to the identified shortcomings.

As part of the study, the author sought to define lethality and recommended that one definition be used across the Marine Corps to ensure a commonality of language. The definition reached by the author is:

> Lethality, as it relates to Marine Corps rifle marksmanship, is the capacity of a system composed of a Marine, the Marine's assigned TO&E [Table of Organization and Equipment] weapon, optics, and ammunition to remove the enemy as a threat during the ongoing mission by achieving a vital hit. This idea of a vital hit is the foundation of Marine Corps rifle marksmanship lethality and is defined as a shot placed on the target in an area resulting in non-reversible injuries, not fully recoverable without care. (McCaleb 2018, pp. 65–66)

In order to calculate the required probability of a hit, the authors needed to measure the accuracy of Marines and their weapon systems and define the size and orientation of the target. The "physical dimensions for target specifications drew from … participant's anthropometric data and the Association for the Advancement of Automotive Medicine's (AAAM) Abbreviated Injury Scale (AIS)" (McCaleb 2018, p. 23) and is depicted as areas on the human body in Figure 7.

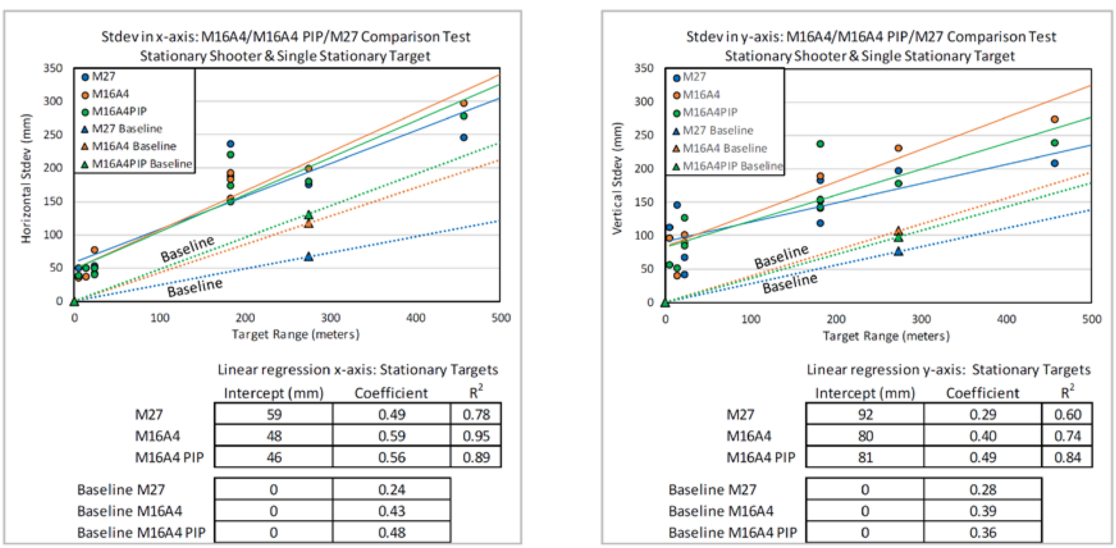


Human musculoskeletal graphic as it relates to the Association for the Advancement of Automotive Medicine's Abbreviated Injury Scale model with color coded 6-point ordinal scale

Figure 7. Abbreviated Injury Scale. Source: McCaleb (2019).

The author of the study relied on two previous studies' data for his analysis, citing that large-scale accuracy data of the type required for the analysis was not regularly collected. The author identified that the variability of the impacts on the target came from the weapon, the shooter, and the environment. In order to separate the variability due to the weapon, the bench test data from a study on weapon performance was used as a baseline. This data came from the *M16A4/M16A4 PIP/M27 Comparison Test Data Report* conducted by the Marine Corps Operational Test and Evaluation Activity (MCOTEA) in 2011. The live fire data was conducted as part of the *Ground Combat Element Integrated Task Force–Live Fire Data*, also conducted by MCOTEA in 2015 (McCaleb, 2018, p. 23). Both previous studies used location of miss and hit (LOMAH) sensors to capture the location of each round’s impact on the target face. The data collected from Marines included 33,081 rounds.

The author chose the standard deviation of the impacts in the X and Y axis separately as the appropriate metric to measure variability based on the different variabilities in the two axes by range, as well as the normal distribution of the data (McCaleb, 2018, p. 25). A linear regression was chosen to model the relationship of the change in standard deviation with range, as it fit the relationship well, and more detailed modeling did not outperform the linear model in a way that justified the added risks in overfitting. The R^2 values for the linear regressions calculated in the study ranged from 0.60 to 0.95 for all weapon variants. (McCaleb, 2018, p. 28). The R^2 is a measurement of the fit of the linear model to the data, with 1 indicating a perfect fit. The standard deviations are plotted against the range in the X and Y axis along with the calculated regression lines in Figure 8.



Linear regression x-axis: Stationary Targets

	Intercept (mm)	Coefficient	R^2
M27	59	0.49	0.78
M16A4	48	0.59	0.95
M16A4 PIP	46	0.56	0.89
Baseline M27	0	0.24	
Baseline M16A4	0	0.43	
Baseline M16A4 PIP	0	0.48	

Linear regression y-axis: Stationary Targets

	Intercept (mm)	Coefficient	R^2
M27	92	0.29	0.60
M16A4	80	0.40	0.74
M16A4 PIP	81	0.49	0.84
Baseline M27	0	0.28	
Baseline M16A4	0	0.39	
Baseline M16A4 PIP	0	0.36	

Linear regression of the x-axis and y-axis standard deviations for the M16A4, M16A4 PIP, and M27 stationary shooter engaging a single stationary target.

Figure 8. Standard Deviation Regression Analysis. Source: McCaleb, (2018).

Next, McCaleb (2018) used simulation to calculate the probability of a vital hit based on the combinations of standard deviations due to a weapon system and range in the X and Y axis. The standard deviations were used to generate 10,000 random normal X and Y coordinates. The authors chose the desired point of aim as the center, and the vital area to calculate the probability of a vital hit for each permutation. In Chapter III, we will repeat this analysis and compare it with the data we observed. A sample visual depiction of the results is displayed in Figure 9.

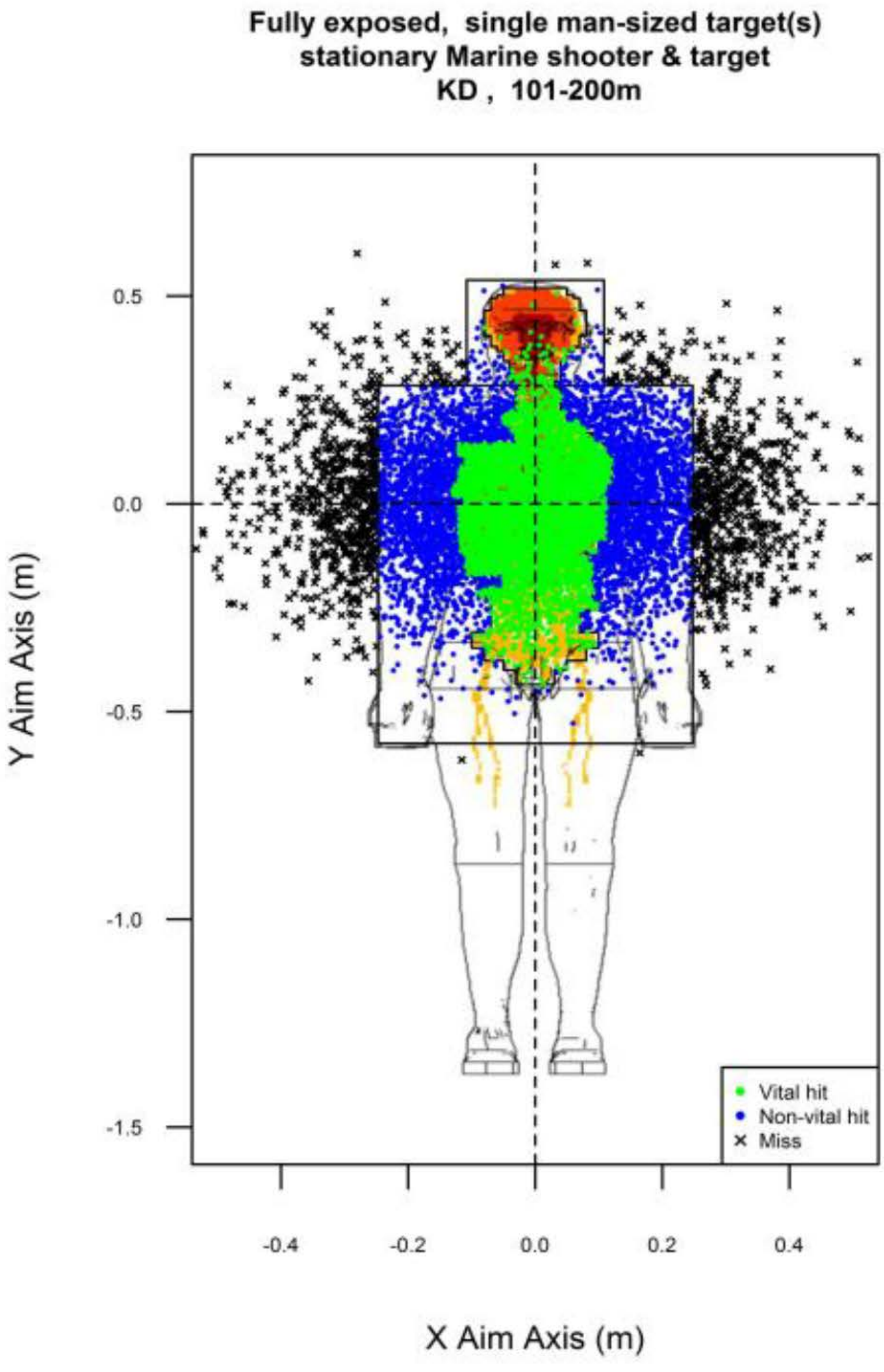


Figure 9. Simulated Impacts on a Single Stationary Fully Exposed Target. Source: McCaleb, (2018).

McCaleb identified an increase in standard deviation, between the benchmark data and the live fire data. This increase and the associated decrease in P_{VH} was attributed by the author to "the shooter's substandard application of marksmanship fundamentals" (2018 p. 47). The author then determined the required decrease in error required to meet the standards. Even when using the most accurate weapon tested, the M27, for a stationary Marine firing at a stationary target, the decrease in shooter induced error required varied from 20% at closer ranges, up to 80% at 200 meters. The required error reduction is depicted in the light blue line in Figure 10. "The required decreases in shooter-induced error for non-materiel solutions range from 10% at 25 meters to 'not possible' or infeasible at 500 meters for a fully exposed target" (McCaleb 2018, p. 56). , Marines will need to improve their marksmanship capabilities through training to remove 80% of the variability beyond that which is attributed to the weapon system alone at the 200- and 300 -yard lines based on the calculated required P_{VH} values.

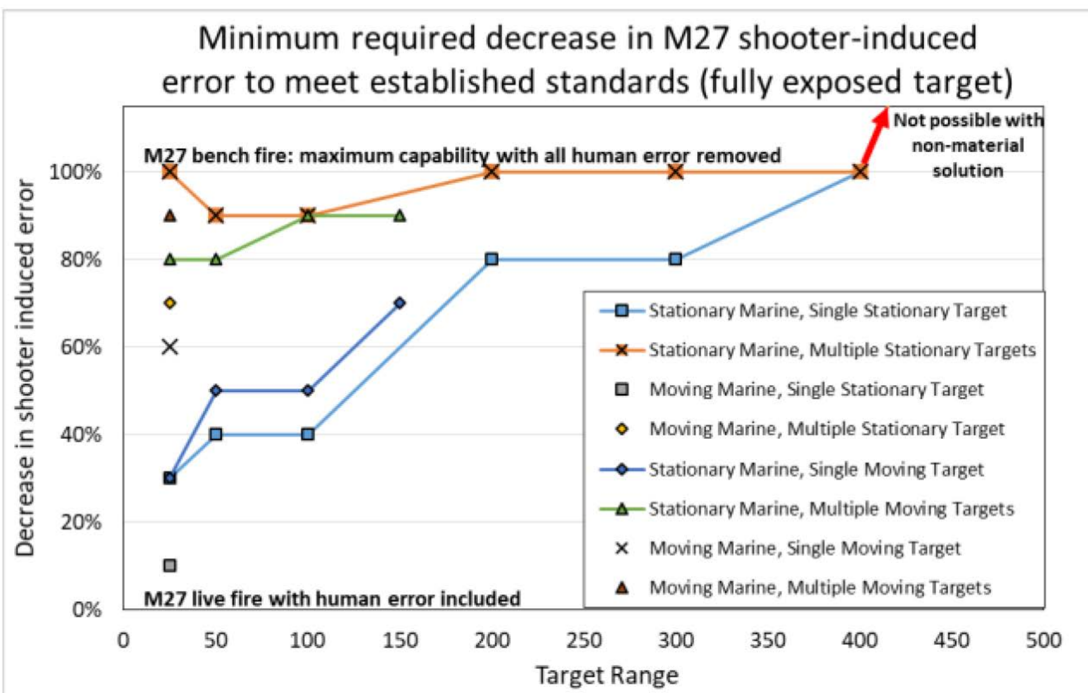


Figure 10. Decrease in Shooter-Induced Error Necessary to Meet the Established Standards. Source: McCaleb, (2018).

The author of the study made recommendations related to training, equipment, and facilities to address the deficiencies in the gaps between the identified required probabilities and the simulated ones. The recommendations applicable to this thesis are the changes in facilities and training. The authors of the study recommended investments in facilities to “provide immediate feedback on round impact, location, and grouping to improve shooter capability and coaching effectiveness” (McCaleb, 2018, p. 58). The feedback provided to the shooters will enable the shooter and the coaches to identify issues and deficiencies. This feedback will aid the shooter’s intuition when evaluating his or her effectiveness. The shooters’ refined intuition will enable “reengagement decisions; point of aim change decisions based on effects on target; and improved shooter capability and coaching effectiveness” (McCaleb, 2018, p. 61). This thesis will refine and develop the tools and analytic infrastructure required to provide the type of feedback recommended by the authors of this study. These tools are the key component to marksmanship training modernization.

“A Marine’s lethal rifle marksmanship capability is defined by the ability to place shots in a vital area, in a repeatable fashion, resulting in an associated probability of a vital hit (P_{VH})” (McCaleb, 2018, p. 66). The goal in marksmanship training is to train Marines to increase consistency, as measured in precision, that is, the size of the cluster of shots on the target, and increase accuracy, as measured by the distance from the center of the shot groups to the center of the target. The methods for measurement and feedback in this thesis will be focused on increasing this capability for individual Marine shooters.

The authors also called for systematic data collection under all conditions for future research. This data collection and analysis will be required to re-evaluate the calculations as training and equipment changes. The author also notes that the “effect of implementing the solutions expressed in this CBA requires continuous data collection and analysis” (McCaleb, 2018, p. 69). Substantial data collection will be required to meet the desired standard identified to calculate the “Predicted probability of hit based on linear regression models for all permutations of aiming technique, firing method, and firing position” (McCaleb, 2018, p. 47). In this thesis effort, we will conduct a similar regression analysis on the calculated X and Y standard deviations for the permutations of range, position, and equipment sets represented in the Table 1A course of fire.

In addressing the training recommendations, McCaleb noted that he did not have access to the data required to determine the effect of training time on marksmanship. "The degree to which a non-materiel solution increases an individual Marine's capability to achieve a vital hit against any of the identified target profiles is difficult to quantify. What is an hour of additional training worth as it relates to increases in precision and accuracy?" (2018, p. 56) In this thesis, we will quantify the increase in performance in terms of precision, accuracy, and horizontal and vertical standard deviation across the three days of training.

3. Predictive Models of User Performance for Marksmanship Training

In 2018, a group of researchers published a paper titled *Predictive Models of User Performance for Marksmanship Training* where they describe their efforts in predicting a soldier's performance on the rifle qualification based on background information on the soldier (Blink et al. 2018). The goal of the paper is very similar to the overall goal of this thesis, to demonstrate the capabilities of modeling if the proper conditions are set and the proper data is made available. The authors state: "This paper reports on our efforts to research the feasibility of collecting, analyzing, and storing data from multiple training systems, in order to accelerate and improve marksmanship training." (Blink et al. 2018, p. 439) "As a demonstration of the usefulness of this data, and in preparation for future work in creating adaptive and personalized marksmanship training systems, we created a predictive model of soldier performance on the standard marksmanship qualification exam and compared the model outputs to actual exam performance" (Blink et al. 2018, p. 439).

The authors used previous research on marksmanship and training techniques to reinforce that "rifle marksmanship is a complex skill comprised of cognitive, psychomotor, and affective components" (Blink et al. 2018, p. 439). The authors used background data along with survey data to build a model to predict qualification performance.

> The input data are attributes in four general categories: demographic, cognitive, psychomotor, and affective. These include survey results,

> simulation training data, self-reported qualification and fitness test results: more than 60 data fields in all. Each trainee also has up to five qualification scores. The highest of these are used to calibrate and validate the models, as only one score is needed to pass qualification, and the highest is used also for soldier ranking. In summary, there are 84 subjects with qualification scores that can range from 0–40, with most scores falling between 20 and 40). Out of this cohort there were (based on the highest qualification score) 10 Experts, 47 Sharpshooters, 26 Marksmen, and 1 UQ (unqualified). (Blink et al. 2018, p. 440)

The models which the researchers produced were remarkably accurate, given the inputs and the relatively small sample size. “These models successfully predicted scores on a 40-point scale with a root mean square error (RMSE) of less than three, using models that are robust to changing input variables” (Blink et al. 2018, p. 439). However, the data set used for the analysis was based on soldiers who were selected for officer candidates, and therefore the data was skewed for high performers. The data set was too small to afford the use of a test set, and the performance of the model was evaluated based on cross-validation. The authors noted only one of the soldiers failed to qualify, and the scores were generally higher than expected. They note that the model may not be accurate on the whole range of soldier performance unless it was rebuilt on a larger data set. “In short, we can’t predict classifications that have only a limited number of examples for our algorithms” (Blink et al. 2018, p. 442). Access to a larger data pool is required improving model accuracy for all shooters. Access to this data was cited as the largest obstacle to implementing a model of this type for multiple reasons. The aggregation of the background data is not a small task and would require deliberate processes to be put in place. “It is possible to repeat this analysis so that both the attribute’s relative contribution to the model as well as the cost of collecting that attribute are taken into account, instead of just the relative contribution alone. (Blink et al. 2018, p. 442).

The authors of the study noted challenges to implementing a model of this type into a training structure, including the availability of the data. The authors noted that marksmanship data was not saved in the level of detail required for effective machine learning models. Additionally, the data is not always accessible to create models to improve training. “One challenge to assessing training effectiveness is a lack of persistent records of soldier performance; too often soldier data are purged shortly after training events for convenience and in order to ensure privacy" (Blink et all 2018, p. 439). The challenges described by the authors also occur with the data collected at CHRC as described by Wheeler (2019).

Of particular interest, the authors of the study did not have access to the coordinates of the impacts of the shots for the ranges they had access to, only the recorded score values. They identified that access to this information would be greatly beneficial in improving marksmanship training. In their section for recommended future work they write:

> For example, a model that predicts performance based on training data collected right before the live-fire certification process will use a different set of attribute weights than a model designed to make predictions before training has even commenced. Also, future models might be built directly based on practice data that takes into account shot X-Y coordinates, in order to produce predictions of failure types and provide formative feedback, both to the trainers and the trainees. Certain patterns that manifest in a trainee's specific shot-by-shot performance might suggest incorrect posture or weapon handling, or might instead display the characteristics of eye-dominance misidentification. Regardless, it is likely that X-Y coordinate analysis of the shot pattern can reveal additional information that is not accessible by the calculated score alone. (Blink et all 2018, p. 442)

With the type of X, Y impact data the authors described, we are exploring the insights possible to be gained in this research. The goals of the 2018 *Predictive Models of User Performance for Marksmanship Training* study are very much in line with the goals of this thesis and serve as a foundation along with the other previously described studies, guidance, and research.

The next chapter provides information about how the data collected for this analysis was collected, organized, cleaned, and used to develop the insights and recommendations provided.

III. AGGREGATE SHOOTER ANALYSIS

A. COLLECTION, COMPILATION, AND DATA PREPARATION

The data was collected at the CHRC, MCAS Miramar in the conduct of routine annual rifle range qualification. The data was generated by an electronic scoring system known as a Known Distance Automated Scoring (KDAS) system. The data was collected to score the performance of the shooters and record their performance in the Marines individual training records. The full data set was exported and compiled as part of research by Wheeler 2019, which enabled data visualization and calculating a lethality metric focusing on individual shooter performance. Due to the scope of the thesis, that effort did not combine the data into a larger data frame consisting of more than one day.

This chapter describes the process used in collecting, transmitting, formatting and structuring the LOMAH data from raw files to a database which can be used to conduct analysis, train statistical models and algorithms, and gain insight into the performance and progress of Marines participating in the Table 1A rifle marksmanship training. In addition to the base R programing language (R Core Team, 2016) we use the library **dplyr** (Wickham et al., 2016) for data manipulation and filtering. The conceptual process is depicted in Figure 11.

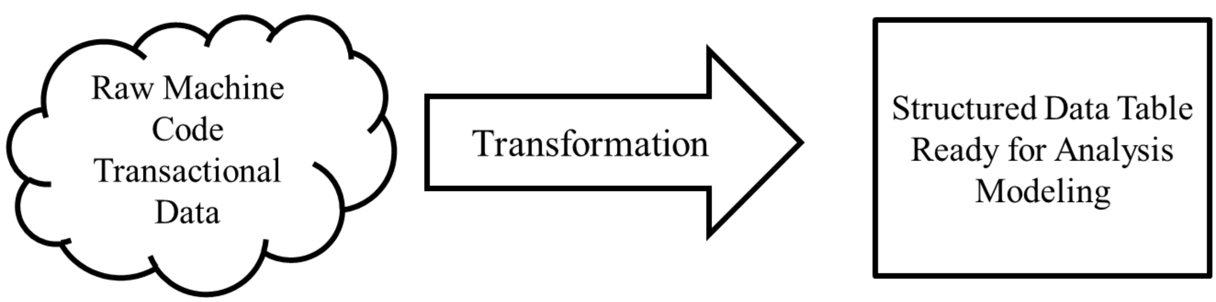


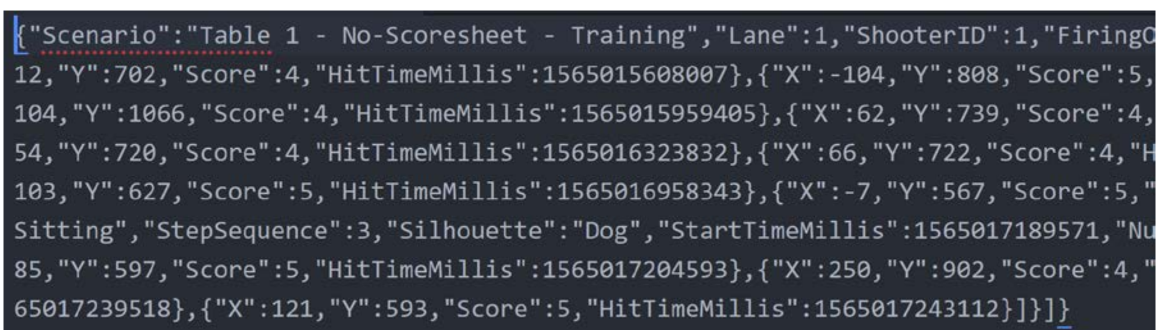
Figure 11. Conceptual Data Transformation Process.

1. Data Source

The data was obtained through a personal relationship developed by Major Wheeler while conducting his thesis research at CHRC. The computer system used to operate the KDAS system does not have the ability to connect to the internet; therefore the data had to be "air gapped." The data was transferred with an external data storage device to a network-connected computer, and then transmitted to a cloud-based file system for analysis. We will provide a recommendation for data transmission in Chapter V.

2. Unpacking

The LOMAH data in raw form is collected in the JavaScript Object Notation (JSON) file format. "JSON is a text format that facilitates structured data interchange between all programming languages. JSON is syntax of braces, brackets, colons, and commas that is useful in many contexts, profiles, and applications" (ECMH 2013). While for the most part, JSON data is human readable, its transactional format is inconvenient for analysis, visualization, and training ML algorithms and statistical models. A screenshot of the data in its raw form is displayed in Figure 12.



{"Scenario":"Table 1 - No-Scoresheet - Training","Lane":1,"ShooterID":1,"FiringC
12,"Y":702,"Score":4,"HitTimeMillis":1565015608007},{"X":-104,"Y":808,"Score":5,
104,"Y":1066,"Score":4,"HitTimeMillis":1565015959405},{"X":62,"Y":739,"Score":4,
54,"Y":720,"Score":4,"HitTimeMillis":1565016323832},{"X":66,"Y":722,"Score":4,"H
103,"Y":627,"Score":5,"HitTimeMillis":1565016958343},{"X":-7,"Y":567,"Score":5,"
Sitting","StepSequence":3,"Silhouette":"Dog","StartTimeMillis":1565017189571,"Nu
85,"Y":597,"Score":5,"HitTimeMillis":1565017204593},{"X":250,"Y":902,"Score":4,"
65017239518},{"X":121,"Y":593,"Score":5,"HitTimeMillis":1565017243112}]}]}

Figure 12. Screenshot of JSON Data as Exported from the KDAS System.

The first tool used to process the data is an "unpacking" function written in the R programming language. This function was developed as part of Wheeler (2019 and was used with small modifications for this thesis. The function loops through all 6,000 plus files in the directory and imports the data. The data is then combined into an R data table and is saved as a Comma Separated Value (CSV) file with the date as a naming convention in format YYYYMMDD.csv. The CSV is a common file format for saving data in a data table like structure with rows and columns. This data type was chosen in Wheeler 2019 and maintained in this thesis for its structure and universal employment. A screenshot of the data as formatted in CSV and viewed in Microsoft Excel is included in Figure 13.

	A	B	C	D	E	F	G	H	I	J	K	L	M	N	O	P	Q
1	Date	DayOfWeek	Scenario	Lane	ShooterID	FiringOrder	FiringOrderStartMillis	Scoresheet	StepName	StepSequence	Silhouette	StartTimeMillis	X	Y	Score	HitTimeMillis	SecondsSinc
2	8/5/2019	Monday	Table 1 - No-Scoresheet - Training	1	1	1	1.56502E+12	NA	Table 1: STAGE 1 -Slow Fire -All Positions	1	Able	1.56502E+12	-130	657	4	1.56502E+12	13.771
3	8/5/2019	Monday	Table 1 - No-Scoresheet - Training	1	1	1	1.56502E+12	NA	Table 1: STAGE 1 -Slow Fire -All Positions	1	Able	1.56502E+12	-12	793	5	1.56502E+12	54.002
4	8/5/2019	Monday	Table 1 - No-Scoresheet - Training	1	1	1	1.56502E+12	NA	Table 1: STAGE 1 -Slow Fire -All Positions	1	Able	1.56502E+12	-97	845	5	1.56502E+12	86.651
5	8/5/2019	Monday	Table 1 - No-Scoresheet - Training	1	1	1	1.56502E+12	NA	Table 1: STAGE 1 -Slow Fire -All Positions	1	Able	1.56502E+12	-12	702	4	1.56502E+12	117.813
6	8/5/2019	Monday	Table 1 - No-Scoresheet - Training	1	1	1	1.56502E+12	NA	Table 1: STAGE 1 -Slow Fire -All Positions	1	Able	1.56502E+12	-104	808	5	1.56502E+12	145.345
7	8/5/2019	Monday	Table 1 - No-Scoresheet - Training	1	1	1	1.56502E+12	NA	Table 1: STAGE 1 -Slow Fire -All Positions	1	Able	1.56502E+12	-153	971	4	1.56502E+12	235.112
8	8/5/2019	Monday	Table 1 - No-Scoresheet - Training	1	1	1	1.56502E+12	NA	Table 1: STAGE 1 -Slow Fire -All Positions	1	Able	1.56502E+12	88	634	4	1.56502E+12	266.451
9	8/5/2019	Monday	Table 1 - No-Scoresheet - Training	1	1	1	1.56502E+12	NA	Table 1: STAGE 1 -Slow Fire -All Positions	1	Able	1.56502E+12	-310	967	3	1.56502E+12	305.356
10	8/5/2019	Monday	Table 1 - No-Scoresheet - Training	1	1	1	1.56502E+12	NA	Table 1: STAGE 1 -Slow Fire -All Positions	1	Able	1.56502E+12	-87	768	4	1.56502E+12	344.039
11	8/5/2019	Monday	Table 1 - No-Scoresheet - Training	1	1	1	1.56502E+12	NA	Table 1: STAGE 1 -Slow Fire -All Positions	1	Able	1.56502E+12	-46	653	4	1.56502E+12	376.666
12	8/5/2019	Monday	Table 1 - No-Scoresheet - Training	1	1	1	1.56502E+12	NA	Table 1: STAGE 1 -Slow Fire -All Positions	1	Able	1.56502E+12	-79	1152	4	1.56502E+12	443.673
13	8/5/2019	Monday	Table 1 - No-Scoresheet - Training	1	1	1	1.56502E+12	NA	Table 1: STAGE 1 -Slow Fire -All Positions	1	Able	1.56502E+12	-104	1066	4	1.56502E+12	469.211
14	8/5/2019	Monday	Table 1 - No-Scoresheet - Training	1	1	1	1.56502E+12	NA	Table 1: STAGE 1 -Slow Fire -All Positions	1	Able	1.56502E+12	62	739	4	1.56502E+12	519.113
15	8/5/2019	Monday	Table 1 - No-Scoresheet - Training	1	1	1	1.56502E+12	NA	Table 1: STAGE 1 -Slow Fire -All Positions	1	Able	1.56502E+12	-28	965	5	1.56502E+12	587.95
16	8/5/2019	Monday	Table 1 - No-Scoresheet - Training	1	1	1	1.56502E+12	NA	Table 1: STAGE 1 -Slow Fire -All Positions	1	Able	1.56502E+12	164	1033	4	1.56502E+12	634.017
17	8/5/2019	Monday	Table 1 - No-Scoresheet - Training	1	1	1	1.56502E+12	NA	Table 1: STAGE 1 -Slow Fire -All Positions	1	Able	1.56502E+12	-426	864	3	1.56502E+12	710.401
18	8/5/2019	Monday	Table 1 - No-Scoresheet - Training	1	1	1	1.56502E+12	NA	Table 1: STAGE 1 -Slow Fire -All Positions	1	Able	1.56502E+12	-276	703	3	1.56502E+12	734.981
19	8/5/2019	Monday	Table 1 - No-Scoresheet - Training	1	1	1	1.56502E+12	NA	Table 1: STAGE 1 -Slow Fire -All Positions	1	Able	1.56502E+12	-59	676	4	1.56502E+12	798.168
20	8/5/2019	Monday	Table 1 - No-Scoresheet - Training	1	1	1	1.56502E+12	NA	Table 1: STAGE 1 -Slow Fire -All Positions	1	Able	1.56502E+12	-54	720	4	1.56502E+12	833.638
21	8/5/2019	Monday	Table 1 - No-Scoresheet - Training	1	1	1	1.56502E+12	NA	Table 1: STAGE 1 -Slow Fire -All Positions	1	Able	1.56502E+12	66	722	4	1.56502E+12	844.461
22	8/5/2019	Monday	Table 1 - No-Scoresheet - Training	1	1	1	1.56502E+12	NA	Table 2: STAGE 2 -Rapid Fire -Standing to Sitting	2	Dog	1.56502E+12	-60	541	5	1.56502E+12	1455.753
23	8/5/2019	Monday	Table 1 - No-Scoresheet - Training	1	1	1	1.56502E+12	NA	Table 2: STAGE 2 -Rapid Fire -Standing to Sitting	2	Dog	1.56502E+12	38	724	5	1.56502E+12	1459.168
24	8/5/2019	Monday	Table 1 - No-Scoresheet - Training	1	1	1	1.56502E+12	NA	Table 2: STAGE 2 -Rapid Fire -Standing to Sitting	2	Dog	1.56502E+12	35	731	5	1.56502E+12	1463.522
25	8/5/2019	Monday	Table 1 - No-Scoresheet - Training	1	1	1	1.56502E+12	NA	Table 2: STAGE 2 -Rapid Fire -Standing to Sitting	2	Dog	1.56502E+12	-103	627	5	1.56502E+12	1468.149
26	8/5/2019	Monday	Table 1 - No-Scoresheet - Training	1	1	1	1.56502E+12	NA	Table 2: STAGE 2 -Rapid Fire -Standing to Sitting	2	Dog	1.56502E+12	-7	567	5	1.56502E+12	1473.279

Figure 13. Screenshot of Formatted Data in CSV Format

The output of this function is a full day of data for over 1,200 "shooter-days" as recorded by the LOMAH system. While the data is imported, the function checks for missing data and formats data fields. This intermediate step was maintained in the process as an excellent opportunity for troubleshooting the importing of the data from the raw JSON data. A visual depiction of this step is included in Figure 14.

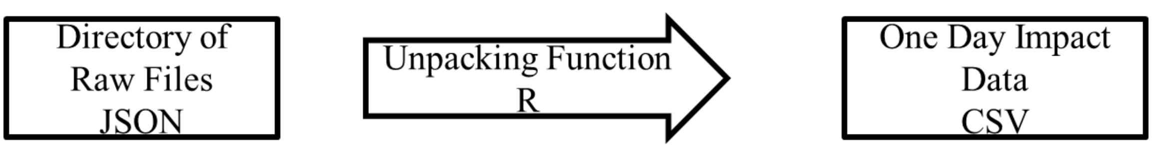


Figure 14. Data Unpacking Process.

In Wheeler (2019), the focus was on individual shooter performance, and there was no need to combine the data into a larger data frame. However, for the analysis required for this study, all the data must be combined into a larger data frame for analysis. In order to accomplish this, we developed a function in the R programming language (R Core Team,

2016) which looped through each .csv file in the directory of single day files and combined the files into one large data frame. As the data was imported, we identified some inconsistencies in the data, and made efforts to “clean” the data. The resultant file was titled “allshots.csv” and includes all the recorded data. In the “allshots” data set each observation, or row is a shot fired, or a record of a shot not taken. The columns, containing the factors, each describe attributes about that observation. A visual depiction of this step in included in Figure 15.

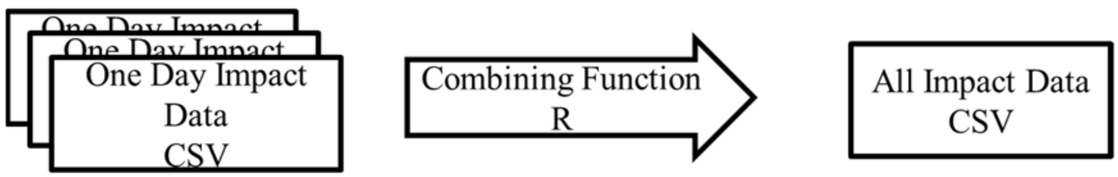


Figure 15. Data Combination Process.

The next section will describe the data set as compiled. We will examine each of the factors of the data as imported from the LOMAH system.

3. Data Variables and Factors

Here are our interpretations and use of each of the 17 factors identified, developed, and inferred in the aggregated data consisting of 330,000 total shots. We used these factors to properly organize the data and facilitate the analysis.

Date. The date the marksmanship training or evaluation was conducted. For the data set compiled for this thesis, we have a total of 26 individual dates with varying numbers of observations on each day. The date is formatted in YYYY-MM-DD format, and is treated as a factor for modeling.

Scenario. The scenario factor identifies the type of training or evaluation the recorded shot was taken under. The scenarios three scenarios included in the data are: “Table 1 - No-Scoresheet - Training,” “Table 1A - Evaluation,” “Table 2 -Evaluation. ” The scenario is roughly analogous to the three types of assessments described in Chapter II, corresponding to the diagnostic, formative, and summative assessments.

The scenario was useful in troubleshooting and setting up the data. The observations recorded with “Table 2 -Evaluation” are excluded from the data set, as they are outside the scope of the analysis conducted. Later in the analysis, a “Training Day” factor is added, which makes the information contained in the scenario factor redundant, and it is replaced in the data set.

Lane. The lane factor indicates which lane the shooter that conducted the training or evaluation was on, corresponding to the 40 lanes or target points at CHRC. The lane number is treated as a factor for modeling, and the effect of the lane on shooter performance is evaluated. The lane number is also used, along with the relay number, in developing an identifying number for each shooter to enable tracking individual performance.

Firing Order. The Firing Order factor is used to capture the “relay” of the shooter. A relay is a group of shooters who all perform the course of fire together at roughly the same time each day. On the CHRC, a relay consists of up to 40 shooters at a time, one on each of the lanes, and up to six relays are fired in a given day. In the data set there are relays on the interval [1,6] and the relay is treated as a factor for modeling purposes. The firing order is also used in the development of a unique ID for each shooter, which will be discussed in the next section on derived factors.

Scoresheet. The scoresheet factor is NA for training sessions and is filled in as “Table 1A” on qualification days when the Marine is shooting for score. This information is used to verify the dates for qualification matched the dates for each detail based on the annual range schedule. Once the data is verified this factor is excluded from further analysis.

Stepname. This factor describes the step or event as it comes from the KDAS. These factors are used to determine the event that the shooter was participating in. “Table 1: STAGE 1 –Slow Fire –All Positions,” “Table 2: STAGE 2 –Rapid Fire –Standing to Sitting,” “Table 3: STAGE 3 –Slow Fire –Sitting,” “Table 4: STAGE 4 –Rapid Fire –Standing to Prone,” “Table 5: STAGE 5 –Slow Fire –Prone.” Number of unique values: 20. The stepname factor as exported from the KDAS system did not provide sufficient level of detail for the analysis we conducted, and it is replaced with a number system described in Chapter IV.

Silhouette. This factor identifies one of three target silhouettes (Able, Dog, B-Modified) and is used as a categorical variable. This factor is used to identify which target silhouette the recorded round was fired on. It is used in the analysis for graphing to ensure that the event is plotted on the correct background for visualization. We also used the silhouette identifier as an easy distinction between the slow fire and rapid-fire events at the 200- and 300-yard lines.

X. The cartesian coordinates of the horizontal impact of the round on the target, measured in mm. Integer. Min: -998. Max: 922. The X-axis is centered on the target center for all target types.

Y. The cartesian coordinates of the vertical impact of the round on the target, measured in mm. Integer. Min: 6. Max: 1856. The Y-axis values were normalized by the target type, setting zero in the Y-axis to the center of the target face, this matches the X-axis, and makes the analysis easier to understand. This process is explained in the next section.

Score. The score corresponds to the value of the round according to where it strikes the target face. Integer. Min: 0. Max: 5. The score is calculated algorithmically by the LOMAH software.

4. Inferred and/or Calculated Factors

Day of Week [Inferred]. The plain text display for the day of the week the training event, inferred from the date. Number unique values: 7. We added this factor for ease of troubleshooting, and for display purposes in the digital databook described in Chapter IV.

Range [Inferred]. The distance between the shooter and the target, measured in yards. This factor was inferred from the listed step name. Integer. Min: 200. Max: 500. Number unique values: 3.

Rounds [Inferred]. The number of rounds fired for an individual event. This number was inferred from the step name with knowledge of the Table 1A course of fire described in Chapter I. Integer. Min: 5. Max: 15. Number unique values: 3.

Shooter ID [Generated]. We generated a unique shooter ID by using a text concatenation consisting of the date, lane, and relay of the shooter. This allowed us to filter out a single individual for a training day. The shooter ID will be used in the single shooter analysis in the next chapter.

Detail [Inferred]. The detail is the group of Marines who train together for the Table 1A, weeklong training event. The detail identifier is a numerical count by fiscal year. We manually added the detail by correlating the detail with the date from the KDAS system. The details used in this analysis are included in Table 1.

Table 1. Range Detail Dates

Detail	Start Date	End Date
34-19	8/5/2019	8/7/2019
35-19	8/12/2019	8/14/2019
37-19	9/9/2019	9/11/2019
38-19	9/16/2019	9/18/2019
05-20	11/18/2019	11/20/2019

Training Day [Inferred]. We added this factor to differentiate the three days of training for each detail. The first date in each detail is training day 1, and the days are numbered sequentially. This factor is used to separate events to determine the effects of training time or practice. Each day aligns with the diagnostic, formative, and summative assessments as laid out in MCDP 7. The training day is used in the single shooter analysis to calculate each individual’s improvements from day to day in Chapter IV.

Detail ID [Generated]. The detail ID allows us to track a single shooter through the progress of the three training days of detail. We generated a unique shooter ID by using a text concatenation using the detail, lane, and relay of the shooter as described in Chapter III. This allowed us to filter out a single individual for a detail.

5. Exploratory Analysis and Data Verification

The data set did not explicitly include units, nor was a data dictionary available. For example, the units of measurement were not included, but were ascertained to be in millimeters. To verify, we filtered the rounds which scored a 5 on the “Able” target and verified the units of the dimensions in the data matched the 12-inch circle of the center ring. We also identified the measurement scheme in the data had the center of the target in the X-axis at zero, with impacts to the left of center assigned a negative value, and those to the right of center assigned a positive value. In the Y-axis, however, the measurement is in millimeters from the bottom of the target. This measurement format creates an issue in comparing impacts from one target face to another because the center of the target is not the same on across three target silhouettes (Able, Dog and B-Modified). These differences are identified in mean vertical impact points when the data is subset by target point, at 887 mm, 740 mm, and 916 mm respectively.

We calculated the center of each target based on the values of the rounds which were scored a five for each target type, and then normalized the data in the Y-axis to form an adjusted coordinate system for analysis. A visual depiction of the impacts for each of the silhouettes is shown in Figures 16 through 18.

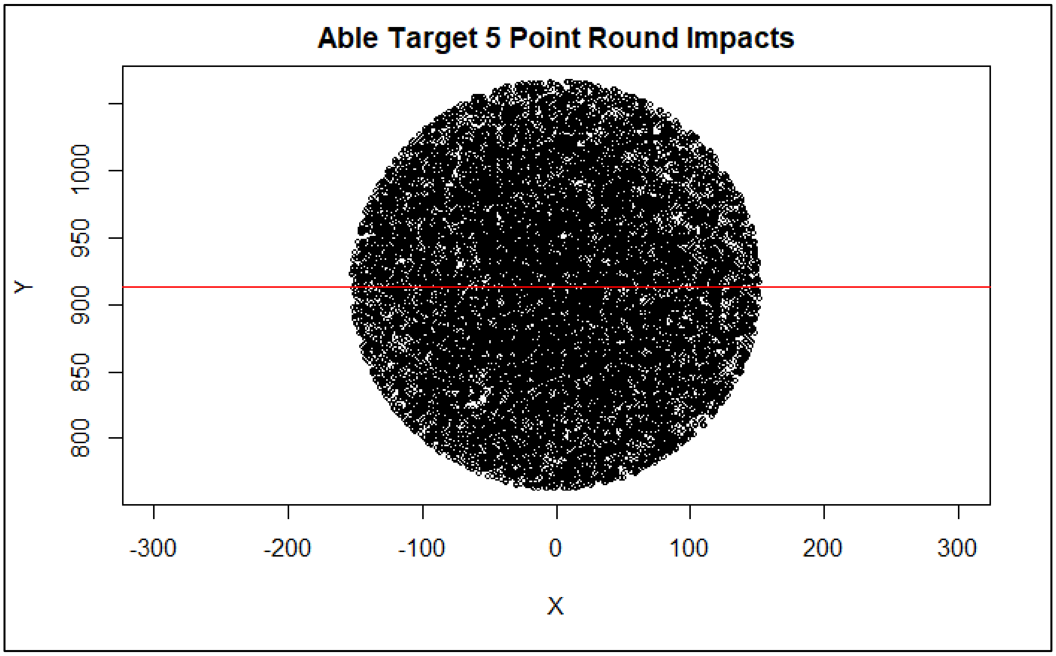


Figure 16. Able Target Five Point Impacts with Vertical Center Marked

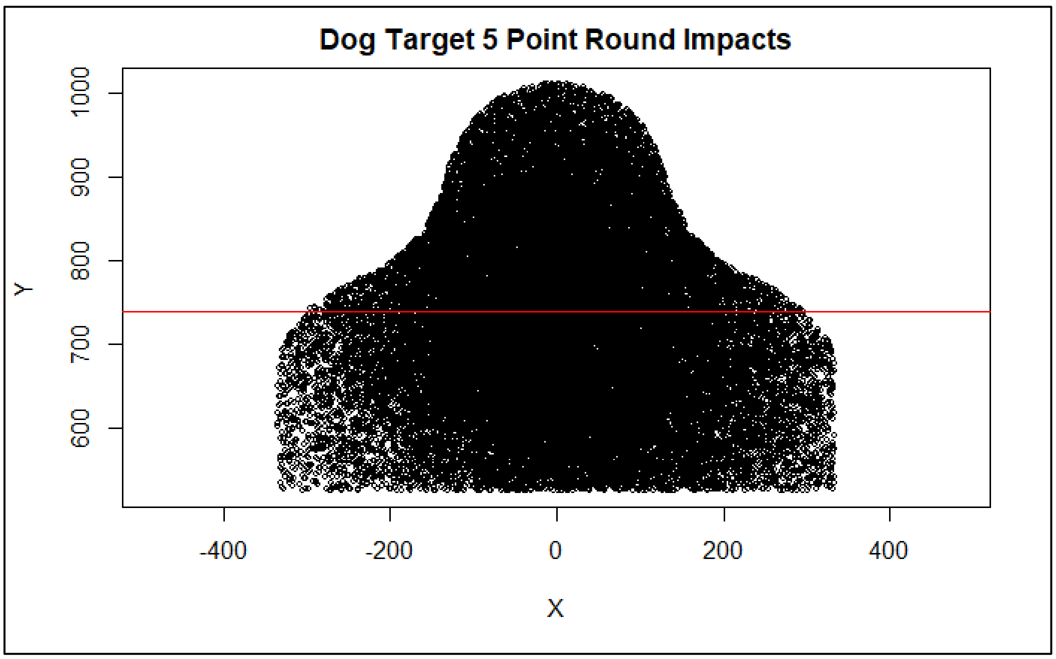


Figure 17. Dog Target Five Point Impacts with Vertical Center Marked

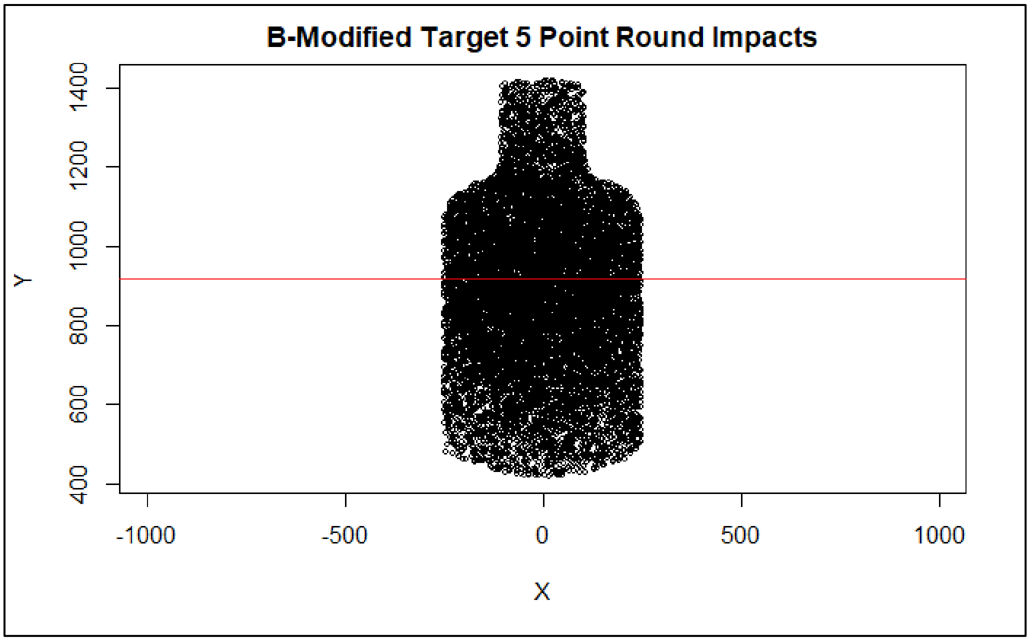


Figure 18. B-Modified Target Five Point Impacts with Vertical Center Marked

Once we identified the center of the - axis for each target we calculated an adjusted Y value for the impacts which we used for the analysis going forward. This new coordinate system gives a convenient (0,0) center point for the center of the target, regardless of the silhouette. The adjusted coordinate system also allows for the comparison of mean vertical (Y) impact points across targets.

B. SUMMARY STATISTICS AND AGGREGATE ANALYSIS

This section will discuss the analysis conducted at the aggregate level, that is all shooters and all rounds impacted under the same conditions, which will be analyzed together. For this analysis, two metrics in the horizontal and vertical planes are useful in understanding the data. First, the mean impact point, which is the average coordinate in the horizontal (X) and vertical (Y) axis. Then the standard deviation of the impacts in both the X and Y axis as a measure of the spread of the distribution of the impacts. In the terms of this analysis, it is desirable for the mean of the impacts to be as close to the center of the target as possible, and the standard deviation to be as small as possible. The formulas for mean and standard deviation are provided in the next section. Collectively we will refer to the metrics calculated as Impact Pattern Analysis (IPA).

$$\overline{X} = \frac{1}{n}\sum_{i=1}^{n} X_i$$

Mean Horizontal Impact

$$\overline{Y} = \frac{1}{n}\sum_{i=1}^{n} Y_i$$

Mean Vertical Impact

$$\sigma_X = \sqrt{\frac{\sum(X_i - \overline{X})^2}{n}}$$

Standard Deviation of Horizontal Impacts

$$\sigma_Y = \sqrt{\frac{\sum(Y_i - \overline{Y})^2}{n}}$$

Standard Deviation of Vertical Impacts

1. Standard Deviation by Range

The first analysis we conducted was a replication of the analysis conducted in the *Lethality CBA* (2018) on this new dataset. We subset the data into groups by range and target type, and modeled the change in standard deviation in the horizontal and vertical directions as a function of range. We chose a linear model for the same reasons as described in the Lethality CBA. Table 2 displays the resulting mean and standard deviation in each axis for each target type and range.

Table 2. Aggregate Analysis Results

Target Type	Range (Yards)	Mean X (mm)	Standard Deviation X (mm)	Mean Y (mm)	Standard Deviation Y (mm)	Observations
Able	200	-12	197	-21	199	48,192
Dog	200	0	167	-30	172	41,444
Able	300	-3	220	-46	234	11,994
Dog	300	20	239	-25	221	39,935
B-Mod	500	-10	329	-2	321	32,522

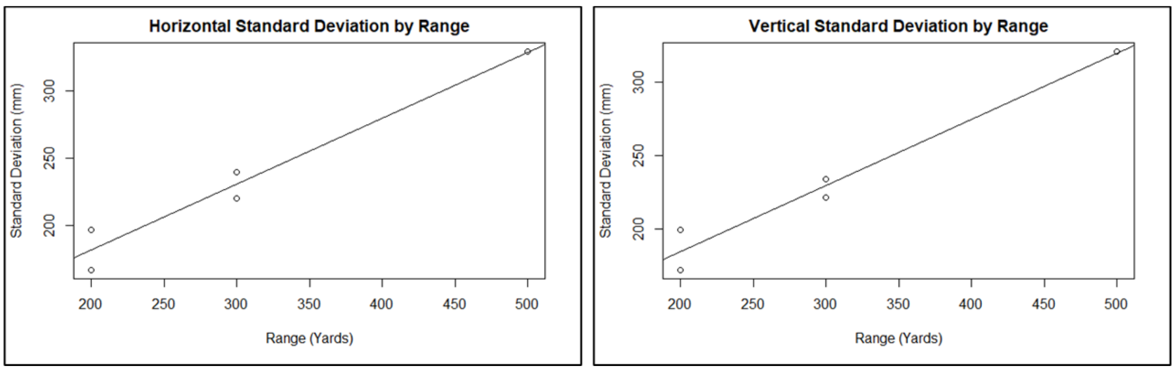


Figure 19. Vertical and Horizontal Standard Deviation by Range Linear Regression

In the linear regression of the standard deviations of the shots by range, shown in Figure 19, we see apparent close correlation between the horizontal and vertical standard deviations with the variability increasing as range increases. The two observations at the 200- and 300-yard lines each show the difference in standard deviations between the slow fire and rapid-fire events. The rapid-fire events have a lower standard deviation in both the X and Y axis at both ranges. R^2 is a measure of fit for a regression model on a scale from zero to one, where a one represents a perfect fit. The intercepts, coefficients, and R^2 values are presented in Table 3.

Table 3. Standard Deviation by Range Linear Regression Results

	Intercept	Coefficient	R^2
Horizontal (X)	83	0.49	0.94
Vertical (Y)	94	0.45	0.95

The general results from our analysis reinforce the analysis conducted in the *Lethality CBA* (2018) and are intuitive. A couple of differences in the analysis are worth noting. In the original study, OAD had information about the specific weapon type employed by each shooter and separated the data points by weapon type. In our analysis, we noted that the standard deviations on the rapid-fire events were lower than the slow fire for the same shooter to target distance. We chose to model the slow fire and rapid-fire events, fired on the able and dog targets, respectively, as separate data points for the regression. The intercepts we calculated at 83 and 94 mm in the horizontal (X) direction, are higher, but in the same order of magnitude of the intercepts calculated in the earlier study. The coefficients, which represent the increase of standard deviation by each additional meter of distance between the shooter and the target were within the range of coefficients calculated for the different weapon types calculated in 2018. The high R^2 values at .94 and .96 values calculated for the linear regression models indicate the models are performing well at explaining the variability in shot impacts due to range.

2. Effect of Training Time

One of the questions posed by Wheeler (2019) in his recommended future work was: “How does practice time affect shooter performance?” (p. 67). We will examine this issue from the aggregate shooter perspective by determining if there is a decrease in the standard deviation of the impacts of the rounds fired under the same conditions (range, target type, rate of fire) across the three days of training. We conduct this analysis by filtering the full data frame by training day, and repeating the analysis conducted in Chapter III. The results of the calculated standard deviations rounded to the nearest mm are included in Tables 4 and 5.

Table 4. Horizontal Standard Deviation by Training Day

Horizontal (X) Standard Deviation (mm)						
Target	**Range**	**Day 1**	**Day 2**	**Day 3**	**Total Change**	**Change Per Day**
Able	200	200	198	197	–2.2	–1.12
Dog	200	172	160	162	–9.6	–4.81
Able	300	219	222	206	–12.7	–6.35
Dog	300	242	231	225	–17.4	–8.72
BMod	500	322	314	296	–26.1	–13.06

Table 5. Horizontal Standard Deviation by Training Day

Vertical (Y) Standard Deviation (mm)							
Target	**Range**	**Day 1**		**Day 2**	**Day 3**	**Total Change**	**Change Per Day**
Able	200	201		192	190	–10.5	–5.24
Dog	200	175		165	168	–7.1	–3.57
Able	300	242		226	225	–17.4	–8.72
Dog	300	222		219	215	–6.8	–3.40
BMod	500	332	313	294	–37.8	–18.91	

As shown in Tables 4 and 5, in all the categories we measured, the shooters as a whole improved, as measured by a decrease in shot group standard deviation, over the three days of training. It was not surprising that the standard deviations that started out larger experienced a greater improvement throughout the days of training.

To test if a trend is present in the data with respect to standard deviation, we conduct a trend test. In the test, the null hypothesis is that no trend is present, and we are equally likely to see an increase or a decrease in each category. The probability is .5 for an observation to increase or decrease. The alternative hypothesis is the probability is not equal to .5. The result of the binomial test is a p-value which is interpreted as the probability that we would see the results as extreme or more extreme than that observed if the null hypothesis is true. We will use a significance level of .05 to interpret the results.

We see that 10 of the 10 categories indicated a decrease in standard deviation, indicating an increase in performance. The probability of this occurring based on the binomial test is examined using the p-value, which in this case equals 0.002, or two in one thousand times we would see such a result if a trend were not present in the data. At a 95% confidence level, we reject the null hypothesis and conclude that yes, shooters improve with training time. This type of analysis can be used to confirm the presence of a trend in the data and confirm that shooters perform and advise the coach more objectively than the methods currently employed.

Next, we repeat the regression analysis for each training day, and plot the results, shown in Figure 20.

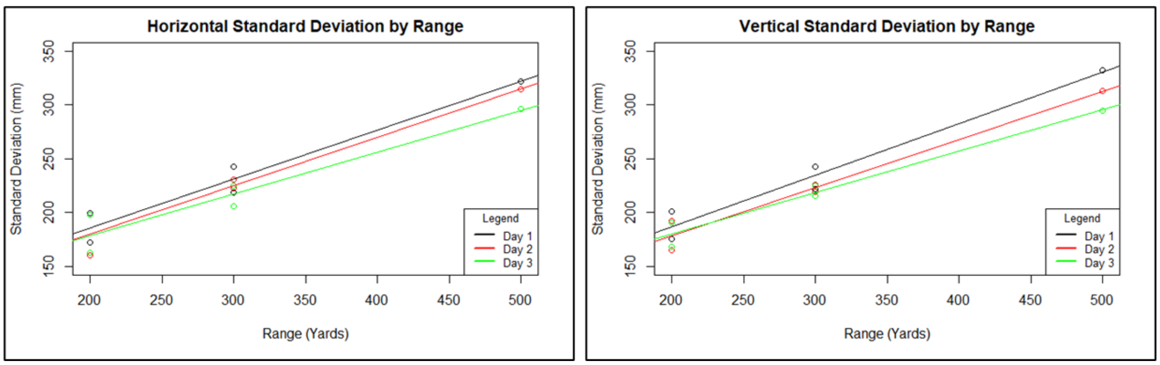


Figure 20. Vertical and Horizontal Standard Deviation by Range, by Training Day Linear Regression

Table 6. Vertical and Horizontal Standard Deviation by Range, by Training Day, Linear Regression Results

Linear Regression Results								
Horizontal (X) Standard Deviation					**Vertical (Y) Standard Deviation**			
	Intercept	**Coefficient**	**R^2**			**Intercept**	**Coefficient**	**R^2**
Day 1	95	0.45	0.93		Day 1	90	0.48	0.95
Day 2	89	0.45	0.93		Day 2	88	0.44	0.96
Day 3	101	0.38	0.89		Day 3	103	0.38	0.96

The increased intercept and decreased slope are an indication of the effect we noticed previously—that the standard deviations that started with a larger absolute value decreased more than those that started out smaller. This disproportionate decrease caused the regression line to pivot at the 200-yard line value and increase the value of the intercept and decrease the value of the slope. The decrease in standard deviation between the first day of training and the qualification on the third day is comparable to the effect of changing weapons from the M16A4 to the M27 at the 500-yard line, as calculated in the *Lethality CBA* (2018). Effectively, and purely coincidentally, the additional practice time of two days lead to the same improvement in standard deviation as the difference between the current most accurate and least accurate weapons in the Marine Corps inventory.

The purpose of calculating the standard deviations and studying the way they change over distance and with practice is to examine the measurement of error in the placements of the shots fired. By gaining a better understanding of the error, we can better identify how to decrease these errors and enhance the lethality of the Marines being trained. We are interested in the standard deviation of the impacts of the rounds as a stand-in for the P_{LH} which is simulated using the standard deviations. A more telling measure of the value of training time would be to put it in terms of the $P_{LH.}$

We have explored the data in aggregate and generated useful descriptive models, which provide insights about the total population of shooters. In the next chapter, we will focus on one shooter at a time and conduct analysis and visualizations to gain insight into an individual's performance. Just as the *Lethality CBA* (2018) examined 33,000 impacts our analysis looked at over 121,000 shots from a different training event revealed improved performance with training and an increase in shot variability with range.

C. DATA VISUALIZATIONS AND ANALYSIS

In this section, we will explore the methods of visualizing the impact data. The first set of visualizations will be histograms generated with the X and Y coordinates of the impacts. By visualizing the data in this way, we can get an understanding of the distribution of the data. We conduct tests for correlation and the distribution of the data.

1. Histograms of Impact Coordinates

The data displayed first is a total of 121,343 observations from all three days of training, across all details, ranges, and all silhouette types. The histograms for the horizontal and vertical coordinates are included in Figures 21 and 22. The histograms are balanced and centered approximately at zero in both axes.

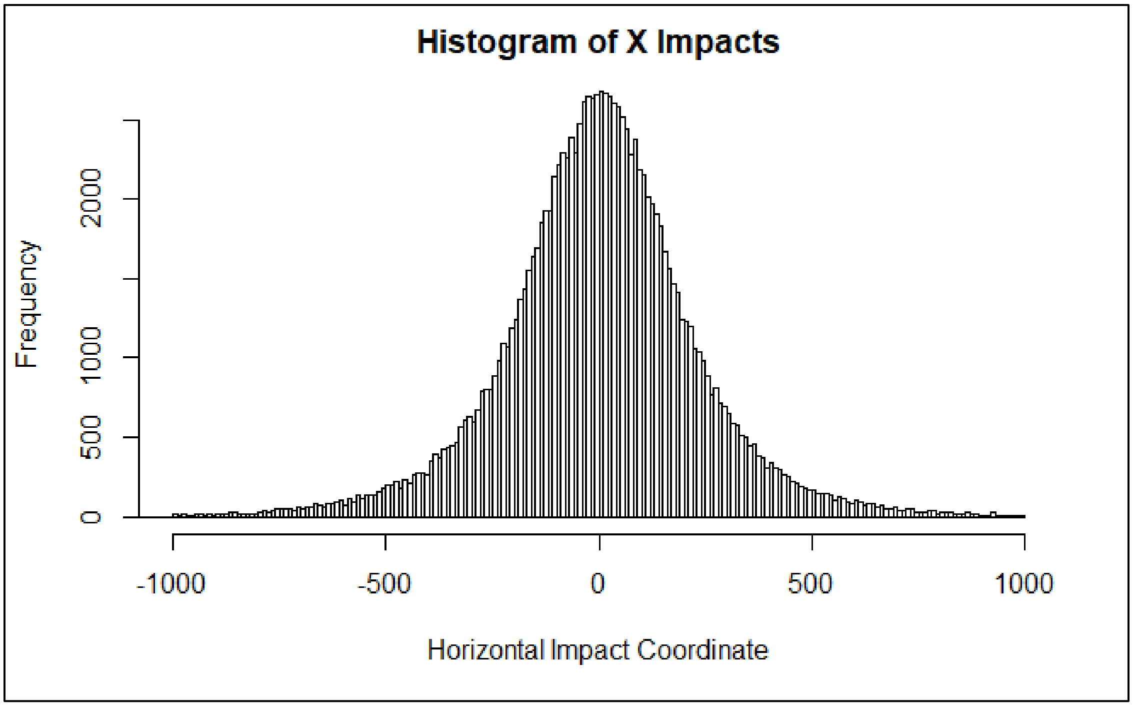


Figure 21. Horizontal Impact Coordinate Histogram

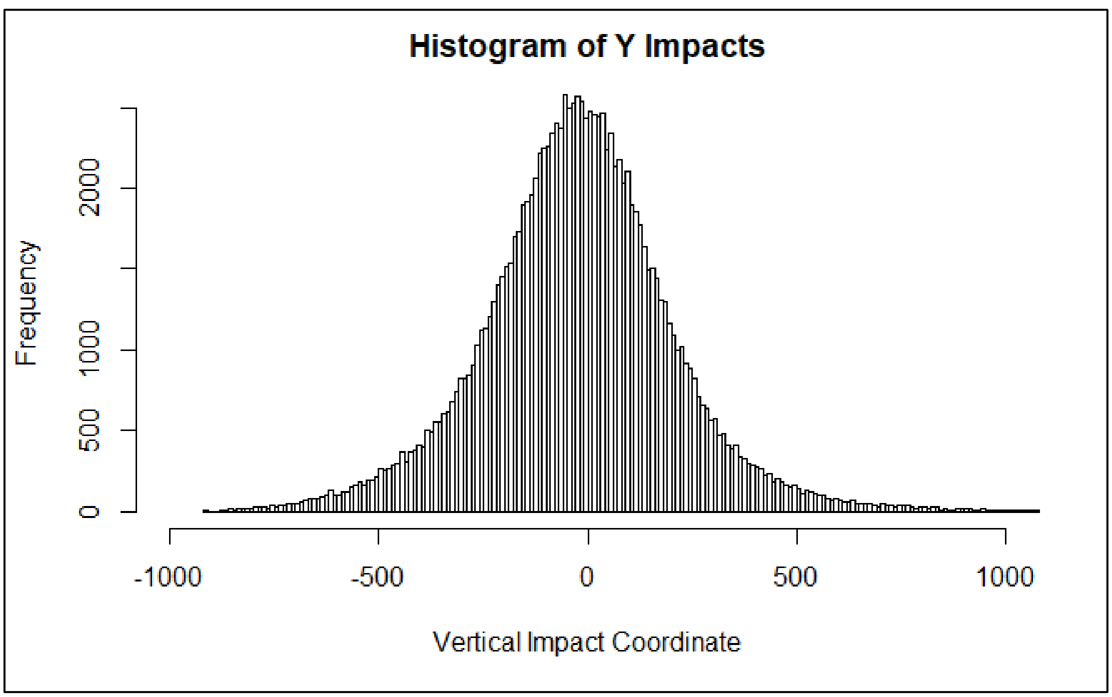


Figure 22. Vertical Impact Coordinate Histogram

2. Normality and Implications for Simulating Probability of Hit

One of the most common assumptions in statistical data analysis and simulation is an assumption that data is normally distributed. This assumption allows for easy calculations of confidence intervals and quantiles and allows for the application of many statistical calculations. It is important to test any assumptions with the data to ensure the results based on these assumptions are valid. In the *Lethality CBA*, McCaleb (2018) assumed that the impacts of rounds were distributed as bivariate normal, with separate standard deviations in the horizontal and vertical axes. This assumption was based on a Shapiro-Wilks test on one subset of the data that indicated the data was, in fact normal.

Ultimately, metrics such as standard deviation, accuracy, and precision are not the measurement of interest in assessing Lethality. As stated in the *Lethality CBA* (2018), the appropriate metric for comparing a shooter's performance to the stated requirement is the Probability of a Lethal Hit (P_{LH}). We sought to repeat the probability calculations for each event to compare the probabilities to the accuracy and precision metrics and use the differences in events to make inferences in the effectiveness of shooting position and rate of fire.

While verifying the assumptions used in the Lethality CBA, we identified that the impact data in our data set violated the normality assumption. Even though the impacts of the rounds are near normal to the eye, by comparing the histograms for each axis to a normal distribution, and the quantiles to a normal quantile, we can detect the departures from normality, particularly in the center, where impacts are more frequent than a normal distribution would suggest.

The impacts for Event 1, the 200 yard-line sitting, slow fire event departed the most from normality, and Event 7, the 500 yard-line, were the closest. Figures 23 and 24 show the histograms for those subsets of impacts, along with a normal curve to show the comparisons, and a QQ Plot comparing the quantiles of the distributions to the normal quantiles with a 95% confidence interval displayed. The presence of observations outside of the 95% confidence interval, and the curved shape of the plot compared to the QQ line indicate a significant departure from normality. The differences are more prevalent in

Event 1, but are observed in Event 7 as well. The histograms were produced with the **hist.default** function (MS Berends, 2019), and the QQ plots with the **qqPlot** function from the package **car** (Fox and Weisberg, 2019).

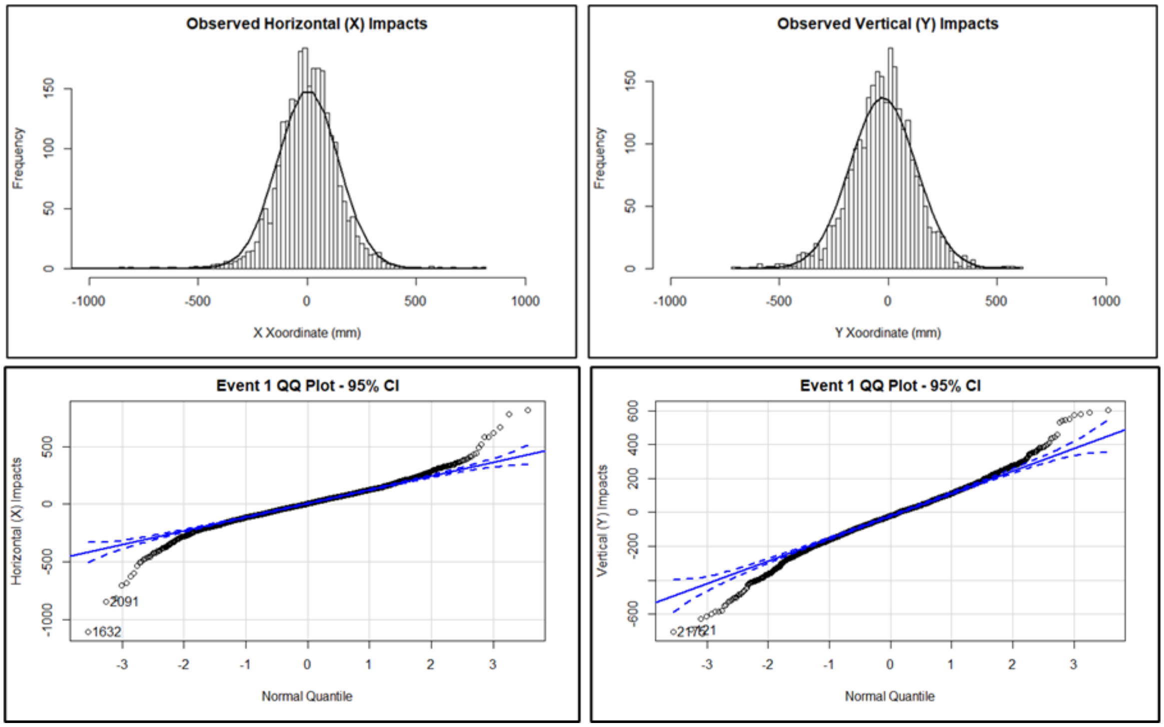


Figure 23. Event 1 Impacts with Normal Curve and Quantile Comparison

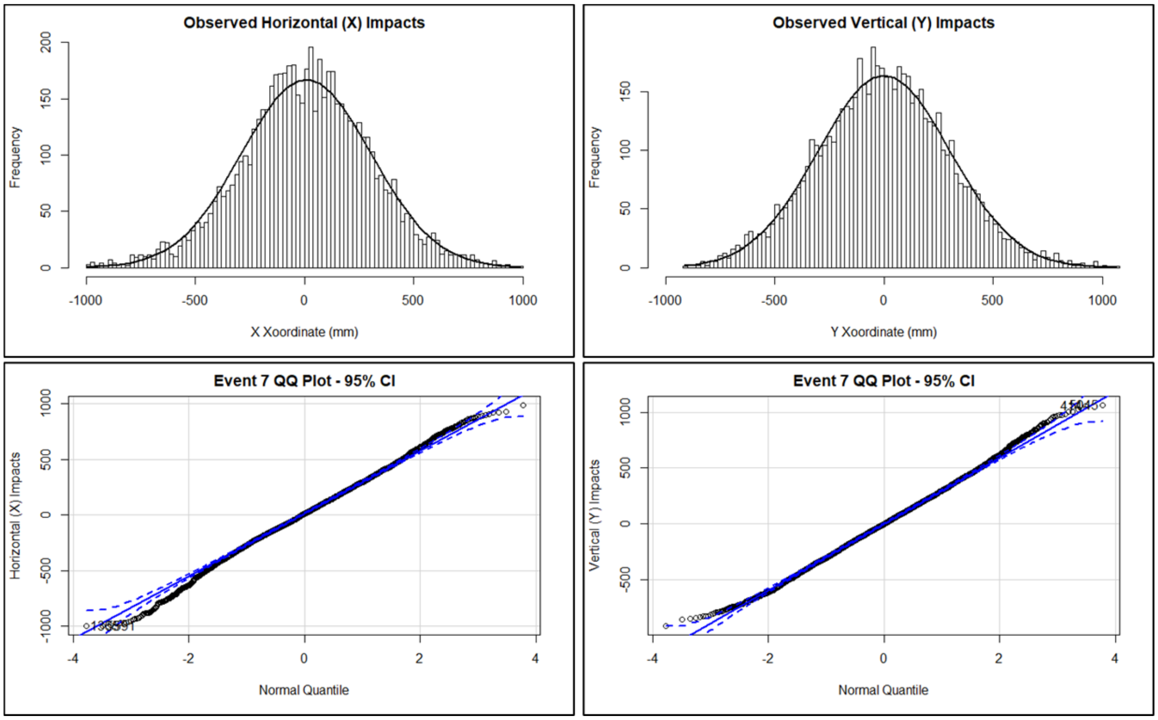


Figure 24. Event 7 Impacts with Normal Curve and Quantile Comparison

Figures 23 and 24 show departures from normality in both sets of data to different extents. To assess the apparent departures from normality we conducted a Shapiro-Wilk test for normality using the base R statistics program (R Core Team, 2016). In the test, the null hypothesis is that the data is normally distributed, with the alternative hypothesis that the data is not normally distributed. We conduct the test at a 95% confidence level. A p-value less than .05 is therefore interpreted that there is evidence present to conclude the data is not normally distributed.

The maximum sample size allowed for the test is 5,000 observations, which is fewer than the number of observations for events 4, 6, and 7. In order to make a fair comparison with all the events, we conducted 10,000 replications of the test on 1,000 “bootstrapped” samples. Bootstrapping is a process by which random observations are sampled from a data set with replacement. We count a test as being significant if the p-value is less than the significance level of .05, and we count the number of significant test results. We then calculate the percentage, displayed rounded to the nearest percent, of the 10,000 replications that were significant. The conclusions of the aggregated tests are displayed in Table 7.

Table 7. Results of 10,000 Bootstrapped Shapiro-Wilk Tests on Each Event

Event	Observations	Significant X	% Significant X	Significant Y	% Significant Y
1	2615	9999	100%	9999	100%
2	2615	10000	100%	9973	100%
3	2615	9607	96%	8089	81%
4	8683	9980	100%	8716	87%
5	2615	10000	100%	9489	95%
6	8687	9954	100%	9903	99%
7	6207	5222	52%	2092	21%

For events one through six, most of the replications indicated that the data was not normal. In order to interpret the results, it is important to consider the context of the tests, with regard to sample size. The tests were conducted on a sample of 1,000 observations. The smaller the sample size, the more likely the test will return an inaccurate result.

The 500-yard line vertical impacts results in the lowest proportion of tests with significant results, indicating the weakest evidence against normality, therefore we conduct further investigation. With 6207 observations available for testing, the test was repeated for another 10,000 times using a larger sample size of 5,000 observations in each test. In this case, all of the tests produced results indicating significant evidence against normality at the larger sample size.

Based on the results, we conclude that the impact data is in fact not normally distributed for any of the events we examined based on the observations available.

Next, we will compare the effect of these departures from normality, and compare the observed data P_{HIT} and the P_{HIT} calculated from bootstrapping and the P_{HIT} from simulation using a normal approximation, as was conducted in the *Lethality CBA* (2018). We generated 10,000 samples of bootstrapped and simulated normal data with the sample standard deviations and repeated the histogram visualizations. The histograms are displayed in Figures 25 and 26 with a line drawn for a normal distribution with the same mean and standard deviation laid overtop for reference. From the histograms, we can see that the actual data and bootstrapped data has the most similar shape with more observations closer to zero and in the tails in both axes than the normally simulated data does. We highlight the departures from normality with red circles and indicate the closeness of fit with the simulated normal data. Note the bootstrapped data more closely represents the actual data than the simulated data in each case.

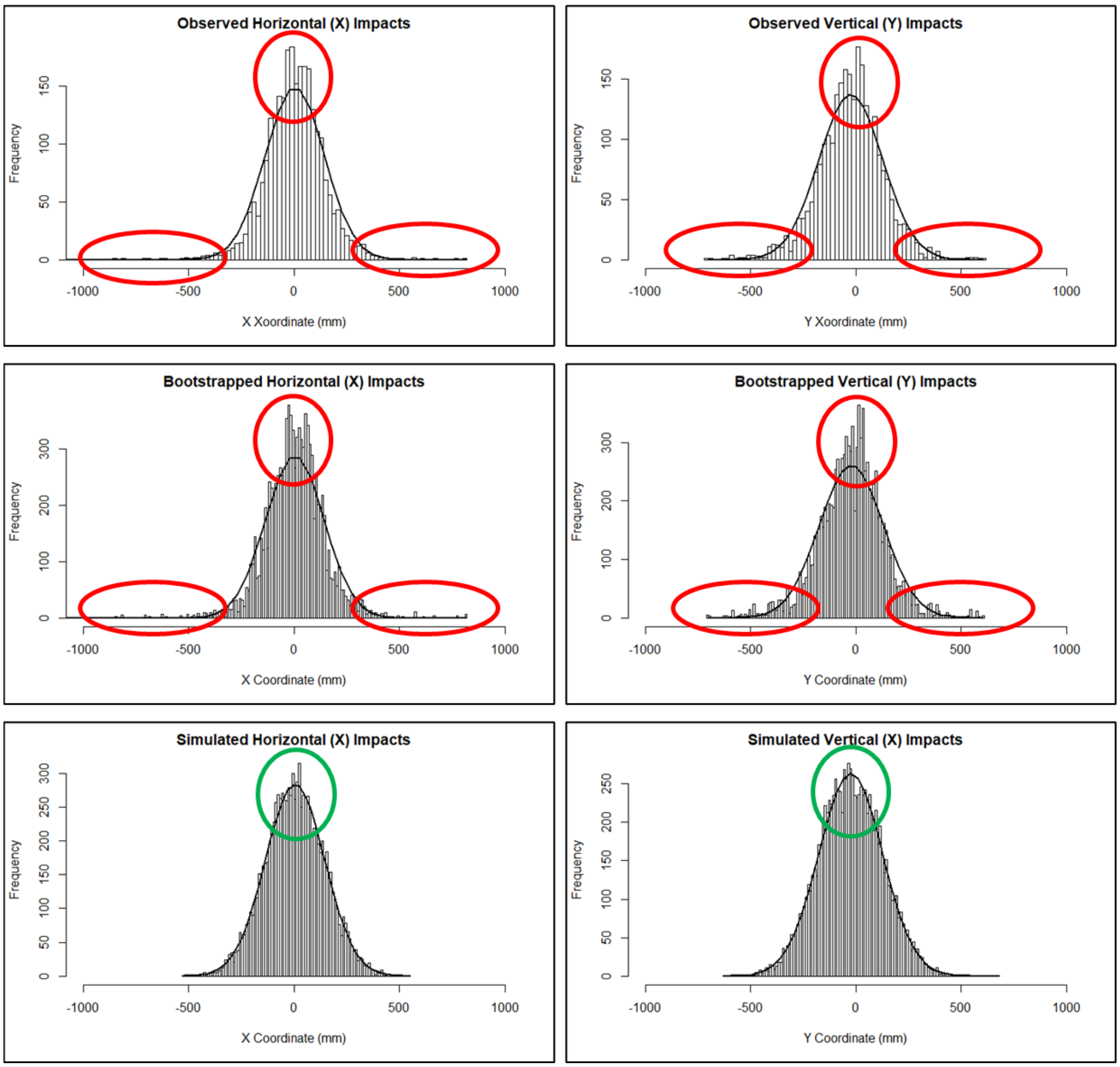


Figure 25. Comparison of Observed, Bootstrapped, and Simulated Impact Histograms, Event 1

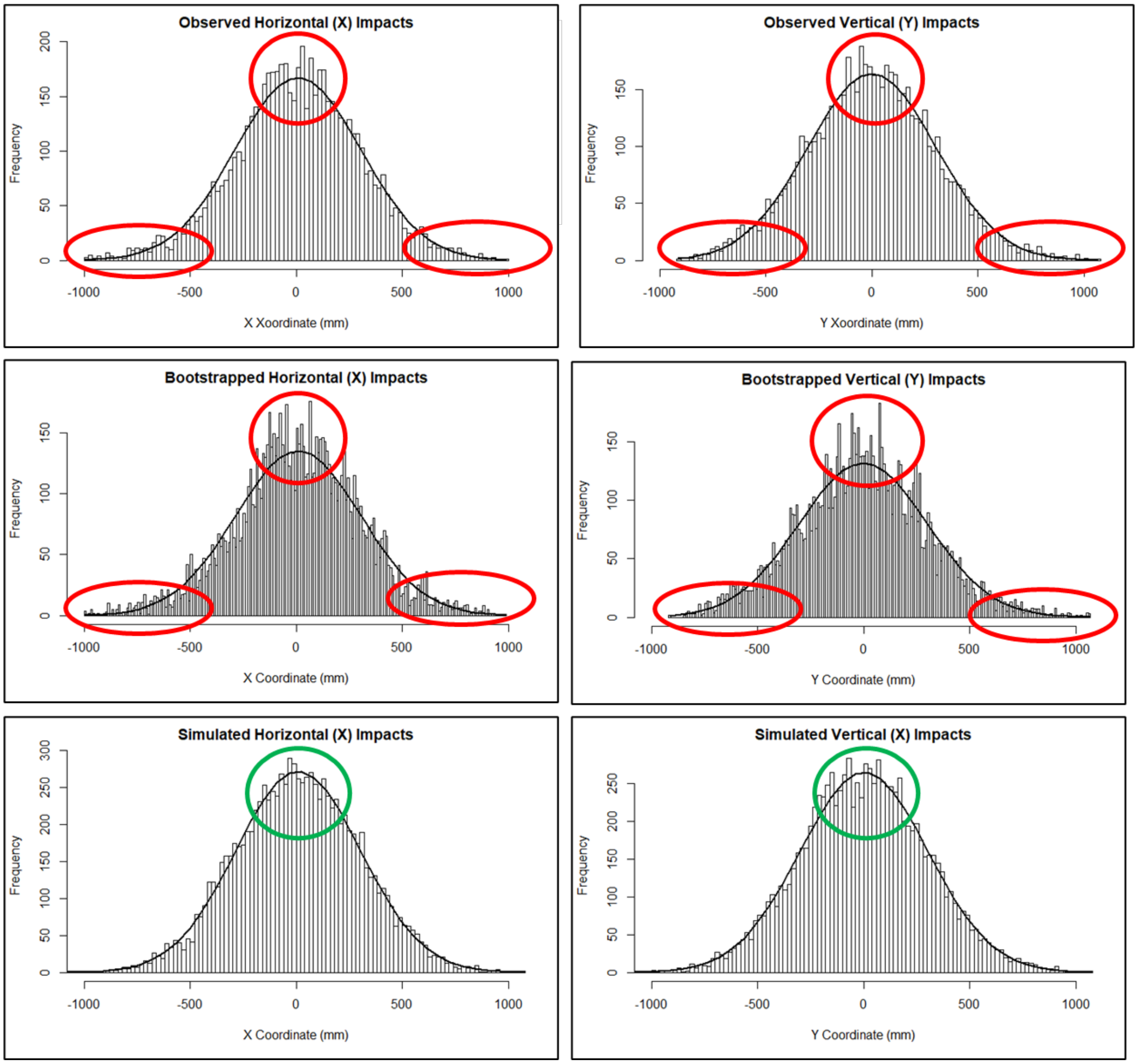


Figure 26. Comparison of Observed, Bootstrapped, and Simulated Impact Histograms, Event 7

The Lethality CBA used the lethal area to calculate P_{LH}. We will use the 5-point center of the Able Target as a stand in metric for same concept to calculate P_{HIT}, for the simplicity of calculation for acceptance and rejection. A hit was calculated using acceptance and rejection if the miss distance was less than or equal to 150mm. This indicates that the round impacted within a 12-inch (300 mm) circle around the center of the target.

To be clear, this differs from the *Lethality CBA* (2018) which used acceptance and rejection on the lethal area, using a more complex acceptance and rejection formula, the specifics of which are detailed in the CBA. The probability of hit values will differ due to the size and shape of the acceptance area, but for our comparison of modeling techniques, this is inconsequential. The results of the observed, bootstrapped, and normally simulated hit percentage calculations are displayed in Table 8. The differences between the values are displayed in Table 9.

Table 8. Comparison of Observed, Bootstrapped, and Simulated Hit Probabilities

Event	Hits	Observations	Hit %	Bootstrap Hits	Bootstrap Hit %	Simulated Hits	Simulated Hit %
1	1335	2615	51.1%	5090	50.9%	4025	40.3%
2	945	2615	36.1%	3602	36.0%	2750	27.5%
3	618	2615	23.6%	2361	23.6%	1973	19.7%
4	3540	8683	40.8%	4037	40.4%	3354	33.5%
5	739	2615	28.3%	2801	28.0%	2240	22.4%
6	2196	8687	25.3%	2518	25.2%	1850	18.5%
7	849	6207	13.7%	1421	14.2%	1178	11.8%

Table 9. Differences in Observed, Bootstrapped, and Simulated Hit Probabilities

Event	Bootstrap Difference	Simulation Difference
1	–0.2%	–10.8%
2	–0.1%	–8.6%
3	0.0%	–3.9%
4	–0.4%	–7.2%
5	–0.3%	–5.9%
6	–0.1%	–6.8%
7	–0.5%	–1.9%

Using bootstrapping, all estimated P_{HIT} values are within 1% of the actual observed value. However, when simulated using a normal approximation, the departure from normality adds to a substantial difference in P_{HIT}, particularly at the shorter ranges. This would lead to an underestimation of P_{HIT} for all ranges, and an increasing error at closer ranges. A comparison graph of the observed, bootstrapped, and simulated P_{HIT} values are displayed in Figure 27. The observed and bootstrapped lines are almost completely overlaid.

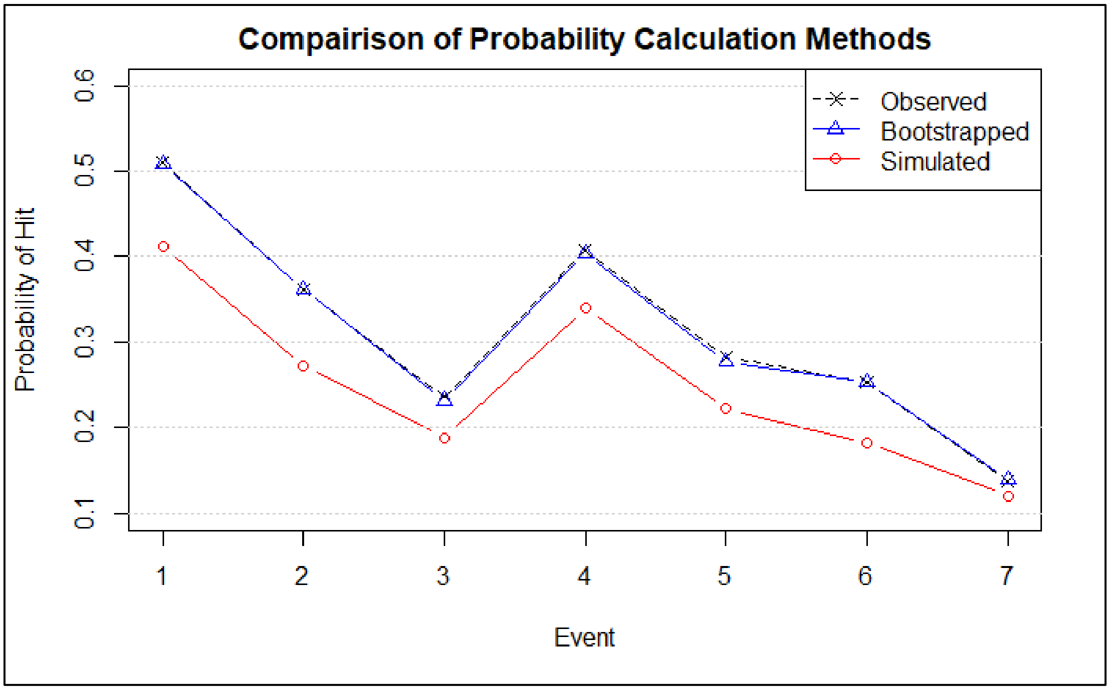


Figure 27. Comparison of Observed, Bootstrapped, and Simulated Hit Probabilities

The *Lethality CBA* (2018) assumed Normality and used that assumption to derive the P_{LH} metric that was used to define the gaps in small arms capabilities. That assumption does not hold on the data we used in this study, which has significant implications for the accuracy of that method in calculating $P_{LH.}$ With the access to the data that would be available with the installation of LOMAH sensors on all USMC ranges, we will be able to more accurately calculate the probability of a lethal hit by bootstrapping actual observations of recorded shots, rather than simulated values. This will lead to better-informed decisions about training, equipment, and tactics.

3. Correlation of X and Y Coordinates

While visualizing the IPA for individual shooters, it appeared that the horizontal and vertical impacts are correlated. To test this assumption, we subset the data for each shooter, and then calculated the correlation. To test the statistical significance of the results, we conduct a binomial test, with a null hypothesis that the probability is .5, and the alternative hypothesis is the probability is not equal to .5. The result of the binomial test is a p-value which is interpreted as the probability that we would see the results as extreme or more extreme than that observed if the null hypothesis is true. We will use a significance level of .05 to interpret the results. We observed that 232 of the 283 pairs of observations having a correlation present. The probability of this occurring based on the binomial test, the p-value = 0. At a .05 significance level we reject the null hypothesis and conclude that yes, the X and Y coordinates of an individual shooter's shots are correlated. The specific correlation varied from shooter to shooter, with the strongest negative correlation calculated at -.51, and the strongest positive correlation calculated to be .31.

4. Correlation of X and Y Standard Deviations

We next plotted the standard deviations in the Y-axis against the standard deviation in the X-axis for each complete event in a subset of the data, and from the appearance from the plot, it appears the values are positively correlated. The pairs plot of the horizontal and vertical standard deviations is displayed in Figure 28.

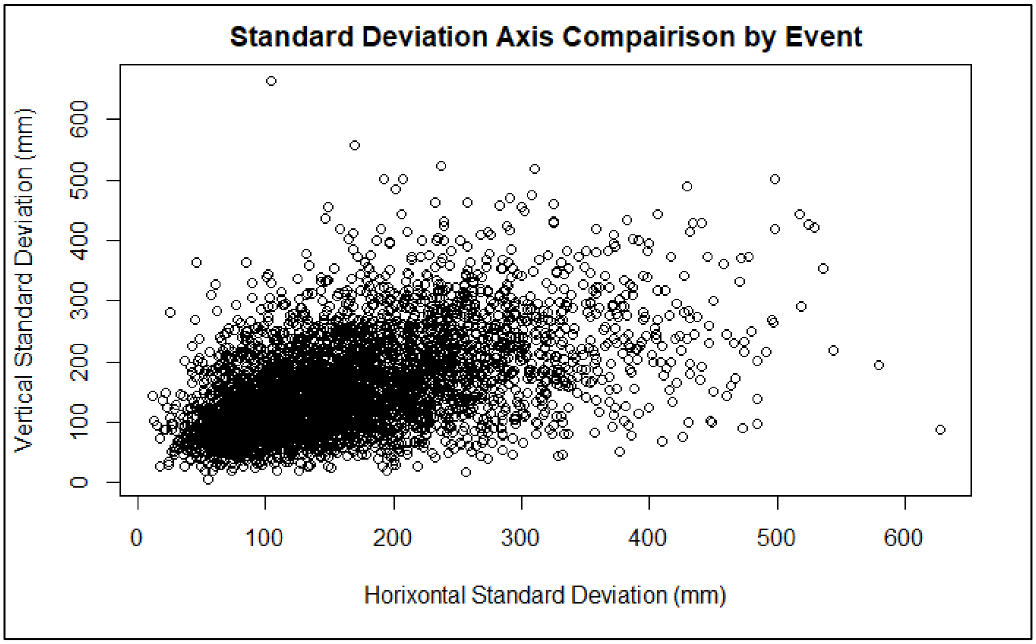


Figure 28. Horizontal and Vertical Standard Deviation Pairs Plot

We conducted a test for correlation based on Pearson's correlation formula in the base R statistical software. The test estimated correlation of .633 with a 95% confidence interval [.601, .663] and a p-value < 2.2e-16 with 1,414 degrees of freedom. Based on the results of the test we confirm that the data does in fact have a positive correlation.

We will display additional data visualizations in Chapter IV when we discuss the distributions of the calculated metrics for each shooter, accuracy and precision.

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IV. INDIVIDUAL SHOOTER ANALYSIS

A. COLLECTION, COMPILATION, AND DATA PREPARATION

In addition to the formulas described in Chapter III, two additional metrics are relevant when studying the IPA of one shooter in one event. The two metrics were used in Wheeler 2019, and are continued in this thesis. A shot “group” is the collective term for the pattern of impacts on a target for an event. In Table 1A, events are 5, 10, or 15 rounds. Accuracy is a measurement of the “tightness” of the group, or “grouping”. Precision is a measurement of the placement of the center of the grouping with respect to the center of the target. A depiction of the difference between high and low accuracy and precision is depicted on the “Dog” target in Figure 28.

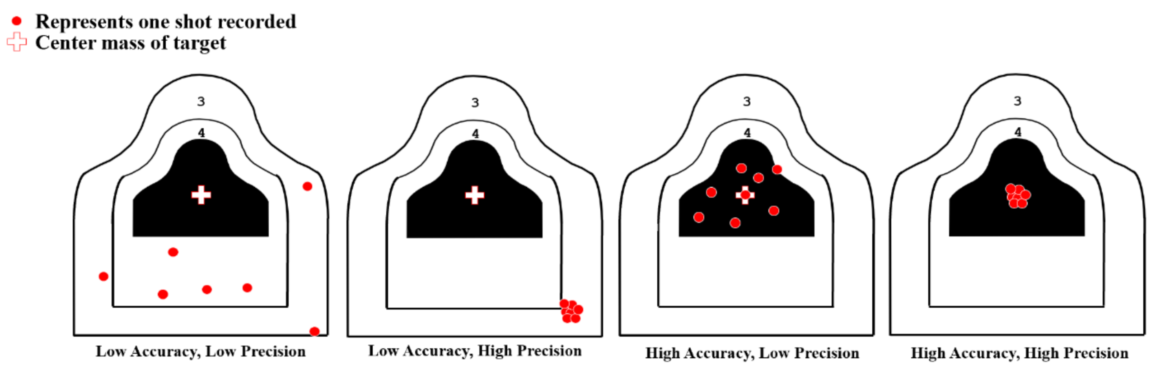


Figure 29. Visual Depiction of the Difference between Accuracy and Precision. Source: Wheeler (2019).

It is worth noting here that the two targets shown in Figure 29 on the right would receive the same score under the current marksmanship program, even though the shooter displayed on the far right is clearly a better shooter. Also of concern, the target second from the left, which demonstrates a very consistent shot grouping would score worse than the shooter on the far left, even though they also demonstrate more precision. The five-point scoring system is inadequate to identify the differences in these hypothetical shooters. Likewise, the use of precision or accuracy alone is insufficient to quantify shooter performance. Both are required to capture shooter performance and each has different skills that have to be mastered in order to shoot with lethality.

1. Accuracy

Accuracy is derived by calculating the center of the shot group for an event, and comparing the center of the shot group to the center of the target. This distance is calculated as the diagonal distance, or radial miss distance, using a variation of the Pythagorean theorem. A lower value is more desirable, as the accuracy measurement is a measure of error. The formula for accuracy is depicted below.

$$A = \sqrt{(\overline{X} - X_0)^2 + (\overline{Y} - Y_O)^2}$$

The accuracy metric is only applicable to rounds fired under the same conditions. For example, in this analysis, we calculate the accuracy for the five rounds fired from the sitting position at the 200-yard line at the able target. Then a separate calculation is conducted for the kneeling position and so on throughout the course of fire.

2. Precision

Precision is calculated by calculating the mean radial miss distance for each round impact from the center of its shot group. A lower value is more desirable, as the precision measurement is a measurement of error. The formula for precision is depicted below.

$$P = \sqrt{\frac{\sum_{i=1}^{n}(\,(X_i - \overline{X})^2 + (Y_i - \overline{Y})^2)}{n}}$$

Just as with accuracy, precision is only applicable to shots fired under the same conditions. We calculate the precision for each of the 27 separate events completed during a Table 1A detail. We describe the events and how they are identified in the next section.

The accuracy and precision measurements are not on the same scale. The accuracy measurement is composed of an error for each axis, and the precision metric is composed of an error for each shot. This is appropriate as the actions required to correct or improve accuracy are taken differently for the horizontal and vertical axis whereas precision is largely a function of applying the fundamentals of marksmanship in position and trigger control.

B. DATA CLEANING

The data set we started with was not originally intended for the purposes of the analysis we conducted. For this reason, there are certain inconsistencies in the data that make analyzing a full three days of data troublesome. First, the sensors are accurate, but no system is 100% reliable. The data set started with over 330,000 observations. If we were to assume 99.9% reliability, we would expect in 330 corrupted observations. The weapons being used to conduct the training are also susceptible to malfunction. If this occurs during training, it is possible a Marine will fire fewer than the prescribed number of rounds or will repeat an event resulting in more rounds recorded than expected. These discrepancies are corrected on the range, at the time of firing, but the log of recorded rounds was not updated.

Each of the roughly 1,200 Marines who participated in the five range details included in the data set is vulnerable to having corrupt, incomplete, or excess data. We first identified discrepancies by not having exactly 210 shots recorded. As we filter for missing observations or duplicate readings, we exclude a larger and larger percentage of the data set. At the end, we are left with 177 complete cases of Marines who we have a full data set across three days of training. This full training data set includes 210 total rounds fired during 27 separate events over three days for a total of 31,170 shots from our original 330,000 shots.

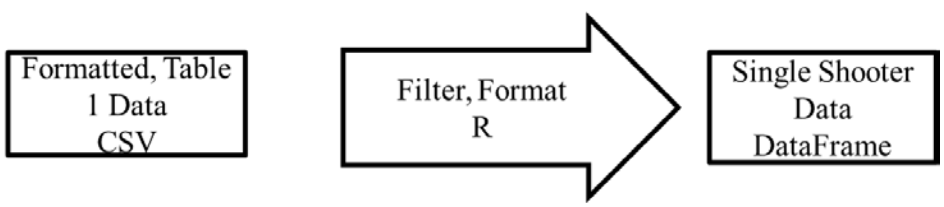


Figure 30. Data Formatting for Individual Shooter Analysis

We used the “DetailID” we developed to filter the data for a single shooter throughout the three days of training. The expected size of the data set is 210 observations, with 80 on the first and second day of training, and 50 on the third day, which is the qualification day where the rounds are recorded for score. The “StepName” factor included from the LOMAH system does not provide sufficient detail for the level of analysis we intended to conduct. For example, a single factor, “STAGE 1 –Slow Fire –All Positions,” is used to differentiate what is actually three different events, shooting at the 200-yard line in the sitting, kneeling, and standing positions. Additionally, on the first two days of training, Marines fire two replications of the “STAGE 2 –Rapid Fire –Standing to Sitting,” which appear as a single event if the data is filtered using the factor produced by the LOMAH system. We were able to fix this issue by deriving new factors in the data set, based on shot sequences for each shooter, that match more accurately the course of fire as described in the *NAVMC 1660*, and shown in Figure 31.

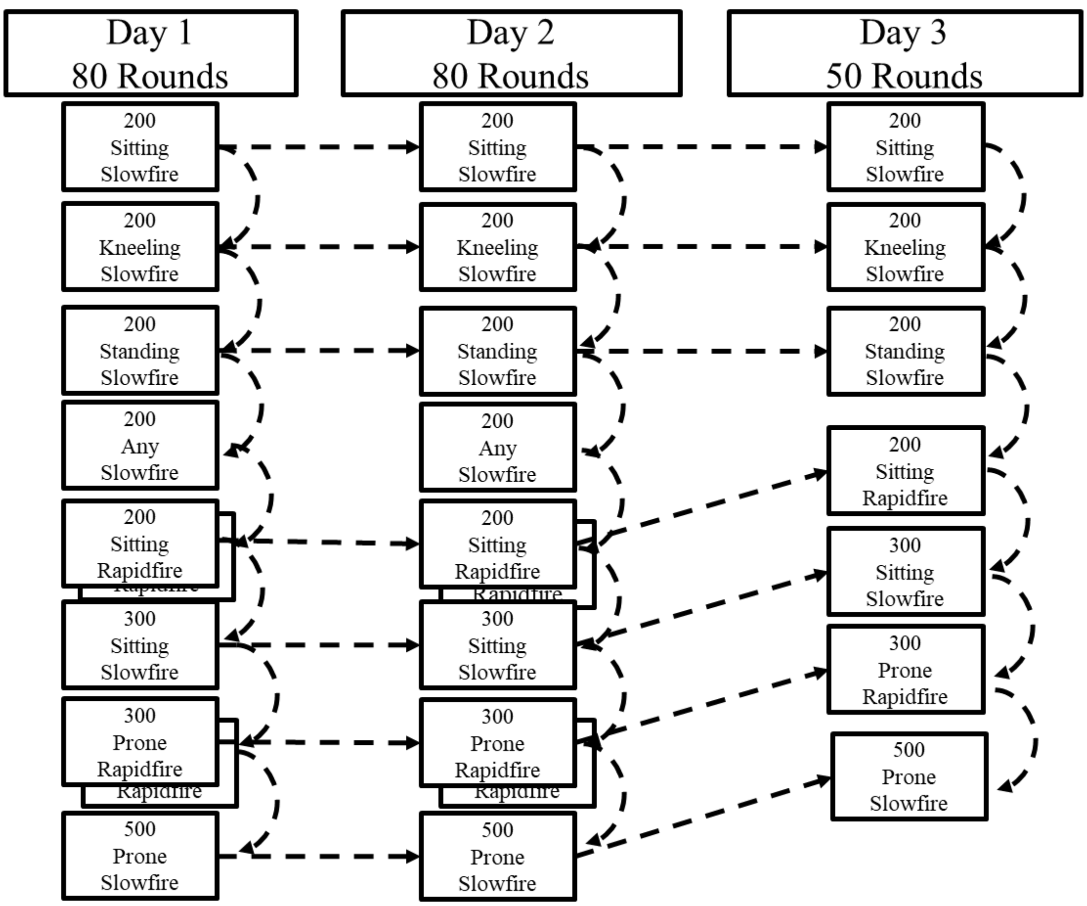


Figure 31. Relationships Between 27 Table 1A Training Events

The additional detail we included in the analysis allows us to not only compare performance on a more "apples to apples" manner, but also allows for more detailed feedback for the shooter and the coach on individual shooting positions. The additional level of detail, breaking out shooting positions and separate runs of events which are repeated, are also necessary to produce the plots which will appear in the digital data book, as described in Chapter V. For the sake of clarity, we will describe an event as a group of shots taken by a single shooter at the same target type, at the same range, in the same shooting position, and at the same rate of fire, on the same day. The three days of training includes a total of 27 events and seven event types, as depicted in Figure 31.

After we subset and organized the data, we are able to conduct analysis on each of the subsets and collect the results. We use the formulas for mean, standard deviation, accuracy and precision as described in Chapter III. The average score per round is included for each event because the number of rounds depends on the event and this is used to standardize the points for the events for the number of rounds fired. A sample of the result of these calculations is included in Table 10.

Table 10. Sample Individual Shooter Analysis for a Full Table 1A Detail.

	Range	Rds.	Shooting Position	Mean X (mm)	Mean Y (mm)	SD X (mm)	SD Y (mm)	Accuracy (mm)	Precision (mm)	Mean Score
1	200	5	Sitting	–25	–69	53	38	74	58	5.0
2	200	5	Kneeling	57	152	168	57	163	159	4.0
3	200	5	Standing	81	–179	92	88	197	113	4.2
4	200	5	Any	–50	–114	40	53	125	59	4.6
5	200	10	Sitting	–11	–109	57	60	110	78	5.0
6	200	10	Sitting	38	–179	62	112	183	122	4.6
7	300	5	Sitting	–49	–151	136	312	158	304	3.6
8	300	10	Prone	26	45	67	84	52	102	5.0
9	300	10	Prone	–26	–61	86	111	67	133	5.0
10	500	15	Prone	36	–147	150	181	152	227	4.9
11	200	5	Sitting	42	–116	58	85	123	92	4.4
12	200	5	Kneeling	43	112	60	78	120	88	4.6
13	200	5	Standing	132	–113	175	109	174	184	4.2

	Range	Rds.	Shooting Position	Mean X (mm)	Mean Y (mm)	SD X (mm)	SD Y (mm)	Accuracy (mm)	Precision (mm)	Mean Score
14	200	5	Any	82	–73	94	32	110	89	4.8
15	200	10	Sitting	–11	–128	82	54	129	93	5.0
16	200	10	Sitting	9	–89	54	105	90	112	4.9
17	300	5	Sitting	36	–55	117	280	66	272	3.8
18	300	10	Prone	35	–123	112	86	127	134	4.9
19	300	10	Prone	125	–98	83	135	159	150	4.7
20	500	15	Prone	123	–246	149	253	275	284	4.5
21	200	5	Sitting	–20	–86	69	50	88	76	5.0
22	200	5	Kneeling	56	11	100	116	57	137	4.8
23	200	5	Standing	–128	–115	182	100	172	185	4.0
24	200	10	Sitting	0	–106	56	72	106	86	5.0
25	300	5	Sitting	57	23	42	227	62	206	4.4
26	300	10	Prone	98	–13	71	115	99	128	5.0
27	500	10	Prone	–55	–64	149	188	84	227	4.9

Table 10 shows that precision and accuracy provide greater fidelity between events where the average score might be the same. For example, Events 1, 5, 8, 9 all have a mean score of 5, but by looking at precision and accuracy we can further distinguish performance on each event. The accuracy measurements for these events range from 52 to 129 mm, and the precision measurements range from 106 to 257 mm. Additionally, the differences in the sizes and shapes of the areas of the target silhouettes make comparisons between events challenging under the current scoring system.

C. VISUALIZATIONS AND ANALYSIS

1. Single Shooter

We visualized the data in different ways to determine the best way to display the differences in the data in a way that would be beneficial to the shooter, the coach, and analysts. We chose a shooter who performed well on all three days to use as the sample shooter for this section. We discovered three effective ways to display the information, by training day and by range. We will begin by examining the standard deviations in the horizontal and vertical directions by range. We will repeat the similar analysis conducted in Chapter III and conduct a linear regression to determine the increase of standard deviation with the increase in range; however, we will take the three training days separately, and conduct individual linear models for each. This will differentiate the change in the data over time. Each of the events will be taken as an observation.

The multiple observations at the same yard line with a varied standard deviation due to the differences in shooting position drives the R^2 values down for these regressions. This is an indication that the shooting position has an effect on the variability of the data, and a linear fit may not be the most appropriate model.

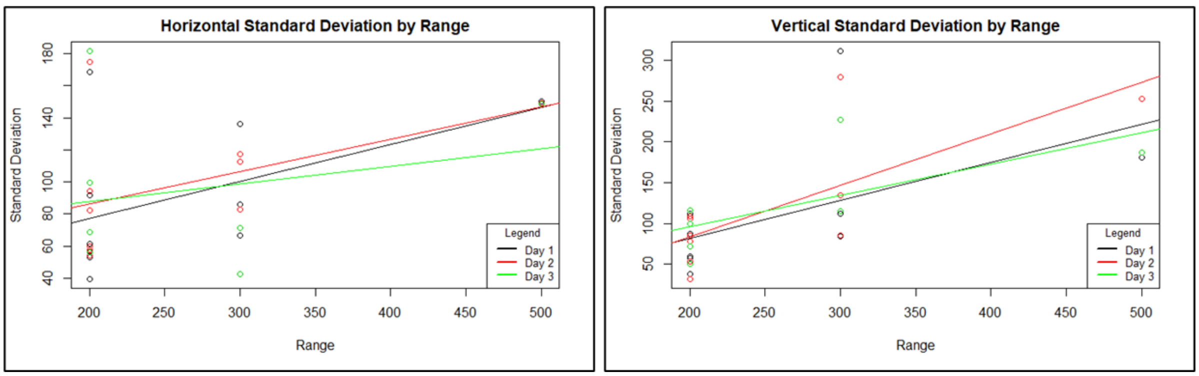


Figure 32. Horizontal and Vertical Standard Deviations by Range with Linear Regression, Single Shooter

Table 11. Horizontal and Vertical Standard Deviations by Range with Linear Regression, Single Shooter

Linear Regression Results								
Horizontal (X) Standard Deviation					**Vertical (Y) Standard Deviation**			
	Intercept	**Coefficient**	**R^2**			**Intercept**	**Coefficient**	**R^2**
Day 1	31	0.23	0.14		Day 1	0	0.46	0.21
Day 2	35	0.20	0.13		Day 2	0	0.63	0.05
Day 3	65	0.11	0.13		Day 3	20	0.38	0.35

We can also use the plot by range to show the change in the average score, the accuracy, and the precision. We continue the color code by each training day to separate the performance on the events by day. A description of the event numbers is included in Table 12. The three graphs are displayed in Figures 33 through 35.

Table 12. Event Descriptions

Event	Range	Shooting Position	Rate
1	200	Sitting	Slow
2	200	Kneeling	Slow
3	200	Standing	Slow
4	200	Sitting	Rapid
5	300	Sitting	Slow
6	300	Prone	Rapid
7	500	Prone	Slow

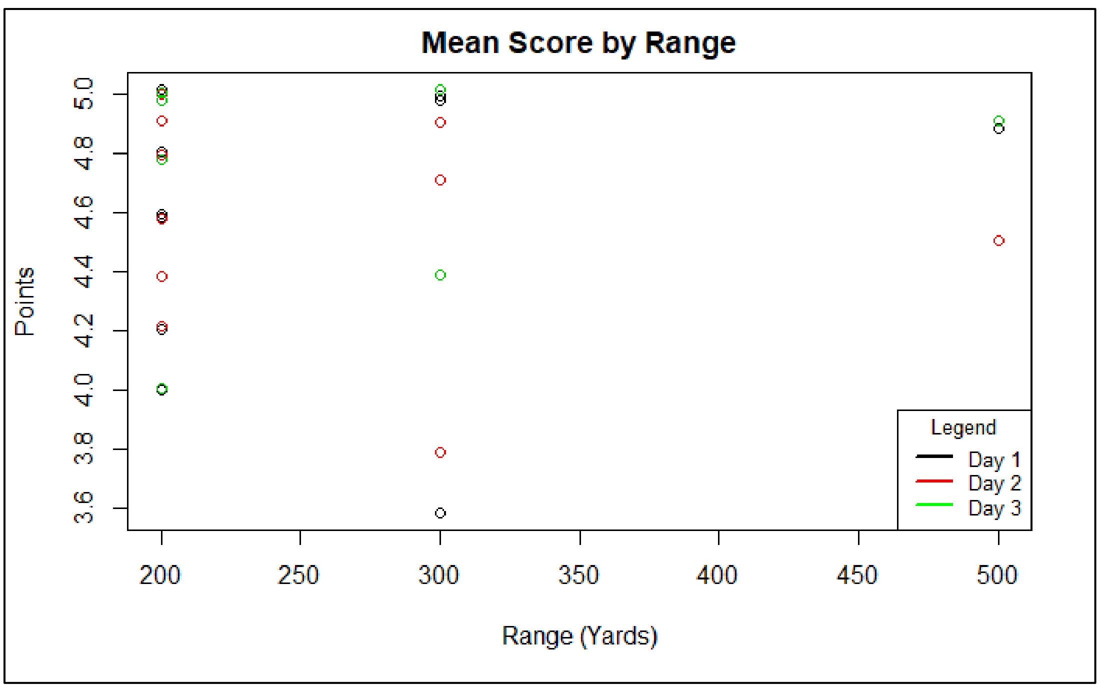


Figure 33. Average Points per Round, by Range, Sample Shooter

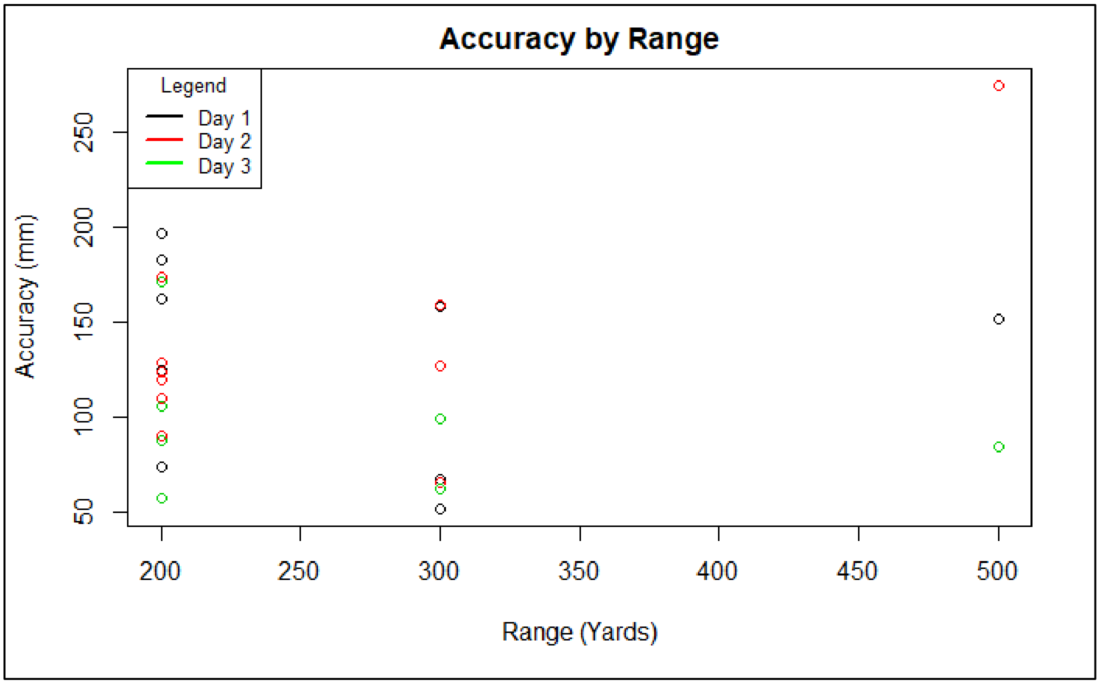


Figure 34. Accuracy by Range, Sample Shooter

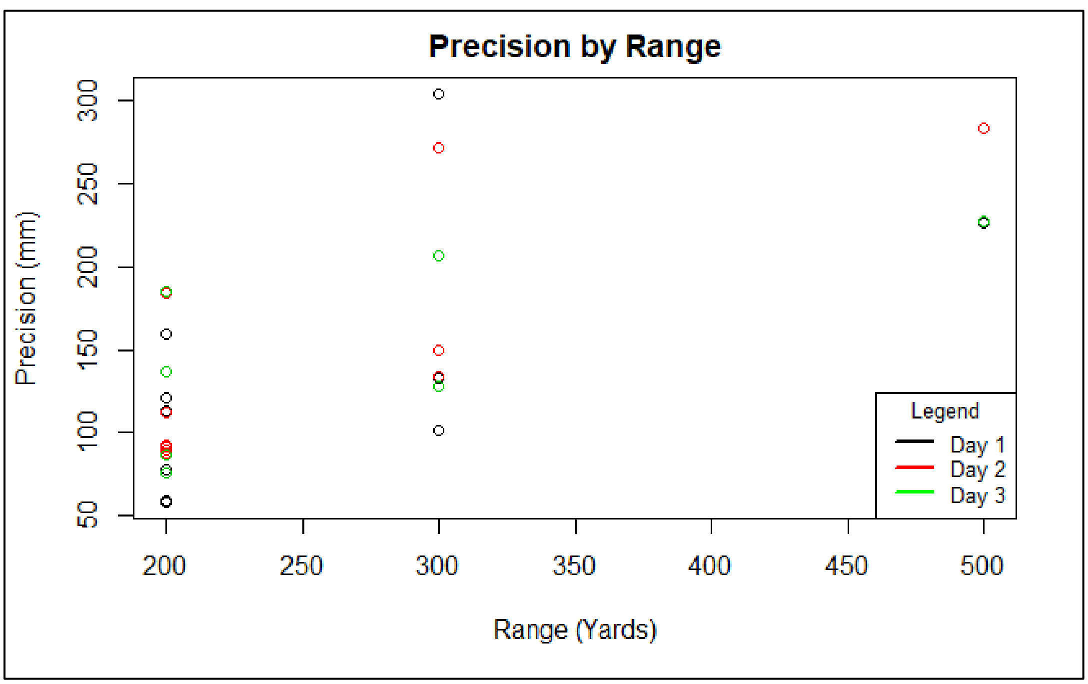


Figure 35. Precision by Range, Sample Shooter

The graph of the precision by range shows that the precision increases with range, generally, this is similar to what we see with the general increase in standard deviation by range. Additionally, the three events in the standing shooting position are clearly worse than the other shooting positions at the 200-yard line for precision. However, range does not have the same effect on accuracy. As we can see the accuracy for this shooter at the 500-yard line is on par with the accuracy at the 200- and 300-yard lines, particularly on the first and third training day. These differences are critical for the type of improvements the shooter needs to focus on and are not accounted for when the data is measured in any other method.

2. All Complete Shooters

Once we identified the calculations to be completed for a shooter for each event, we repeated the analysis on all the shooters with a complete data set. A total of 15 data fields were captured for each event, resulting in a data frame with 4779 rows and 15 columns. From this data, we can gather insight on the distributions of the IPA metrics for each event type.

Figure 36 displays the histogram of all of the accuracy measurements for each event calculated. We can see the distribution is skewed left, with a long tail to the right. The mean accuracy measurement is 160 mm.

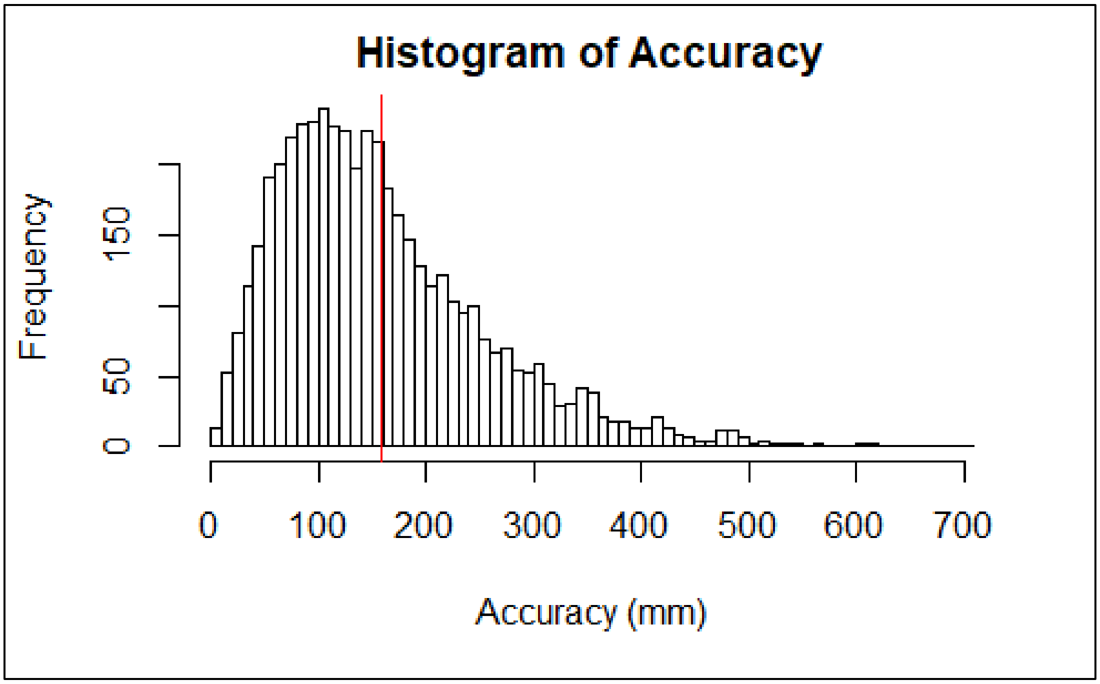


Figure 36. Histogram of Accuracy Across all Events

Figure 37 displays the histogram of all the precision measurements for each event calculated. We can see the distribution is skewed left, with a long tail to the right. The mean accuracy measurement is 205 mm.

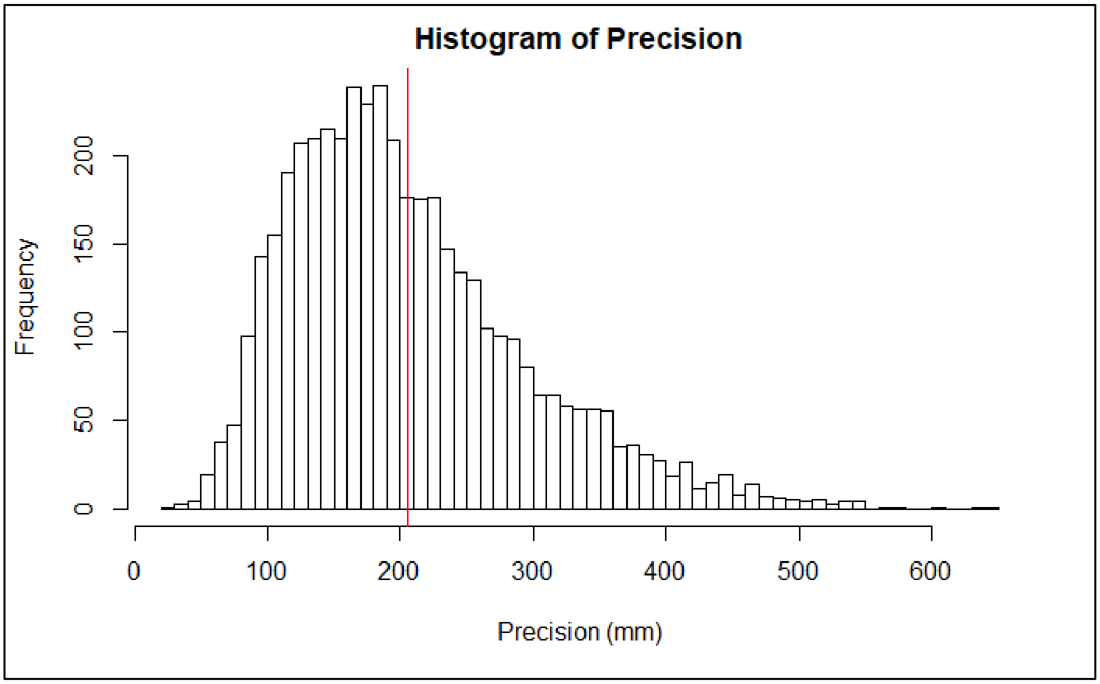


Figure 37. Histogram of Precision Across all Events

Figures 38 and 39 show the distributions of the Horizontal (X) and Vertical (Y) standard deviations. Both are skewed left, with a similar shape to the accuracy and precision distributions. However, the mean values are 162 mm and 156 mm, respectively.

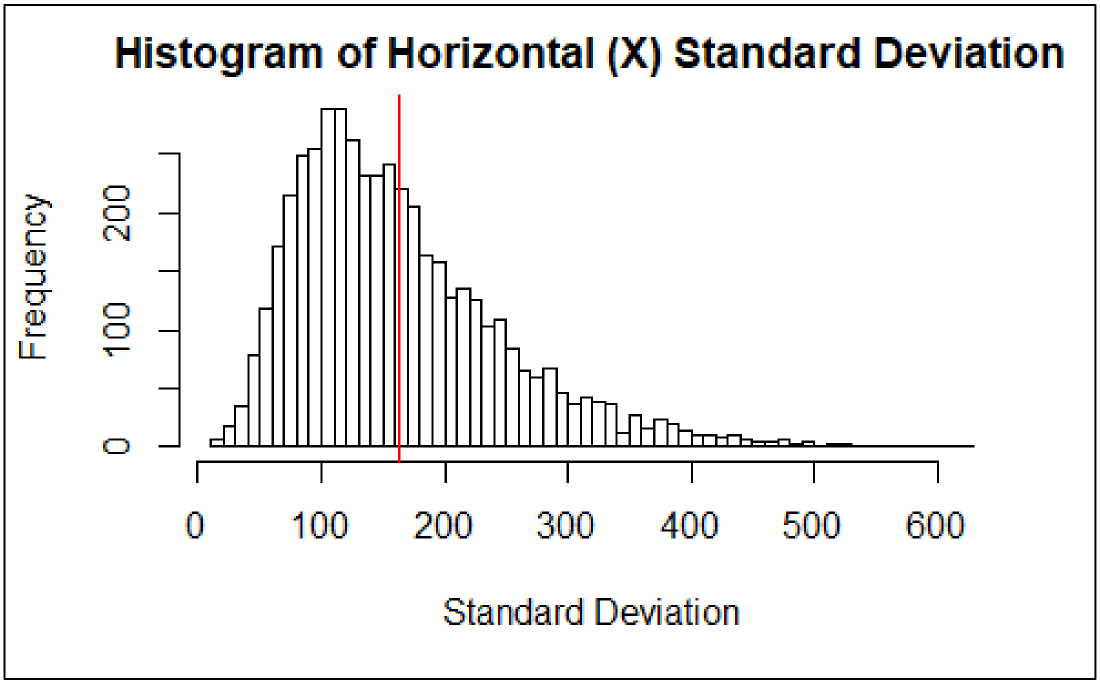


Figure 38. Histogram of Horizontal (X) Standard Deviation Across all Events

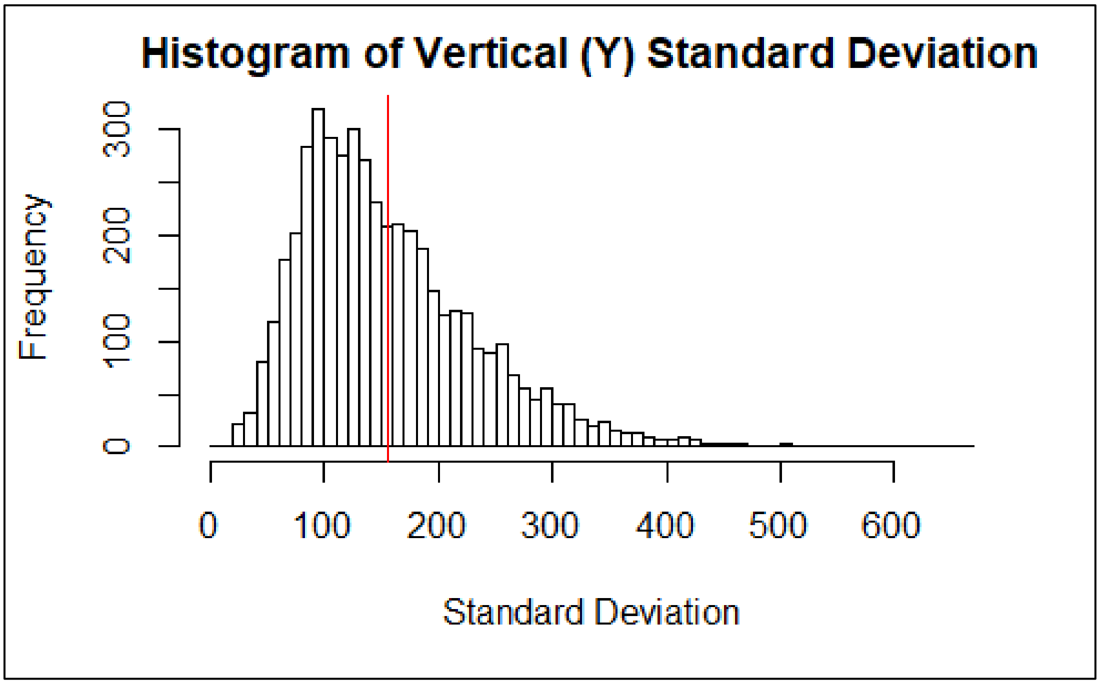


Figure 39. Histogram of Vertical (Y) Standard Deviation Across all Events

The final histogram of the group, Figure 40, shows the distribution of mean points per round for each event. The distribution is skewed like the previous distributions; however, the mean score is skewed right. This is in the same direction in terms of the desired value; however, it is reverse of the previous distributions. The mean value is 4.1 points per round. On a five-point scale, we can see that the mean is surprisingly high. It is important to note that the values for each round are discrete; however, each event has between 5 and 15 rounds so fractional point values are calculated for the mean of each event.

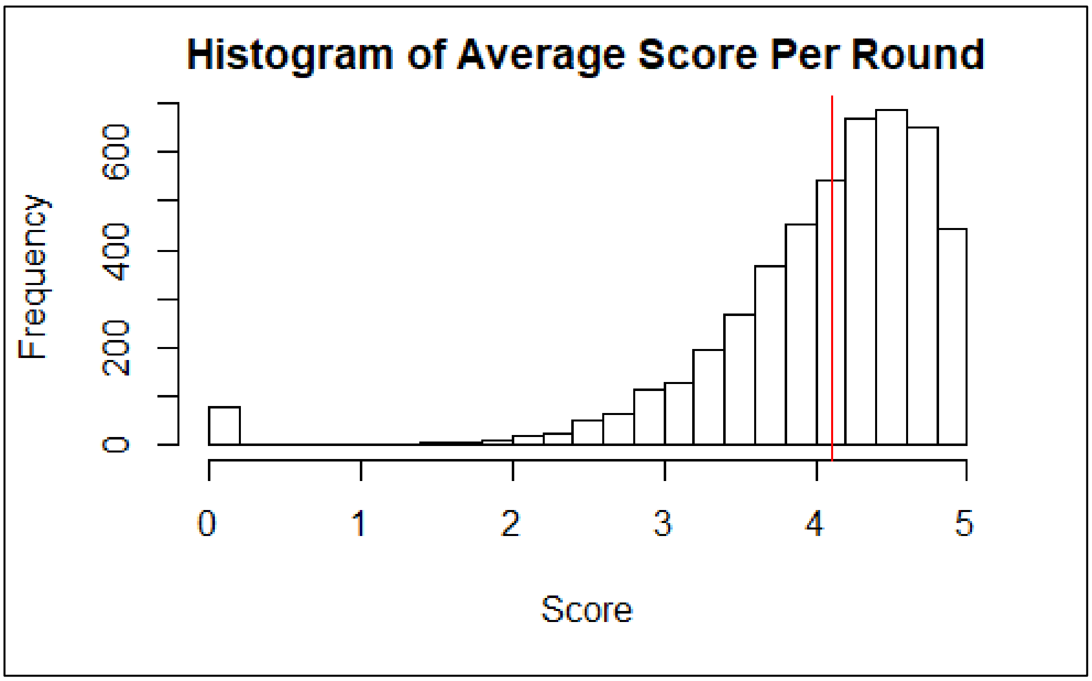


Figure 40. Histogram of Average Score Per Round

D. COMPARISON OF METRICS

> Using metrics with greater fidelity … we can seek to optimize quantity and quality of practice time to increase proficiency to a desired threshold. Alternatively, other factors could be isolated and used as a measure of enhanced performance on a rifle, dependent on the amount of time spent practicing on the range. More investigation into the results produced by shooters on the range, using varied amounts of practice time, will provide better insights on the ideal practice time requirements.
>
> —Major Kevin Wheeler, 2019

In order to understand the relationship between the various measures for an event, first we develop a correlation matrix for the IPA metrics and the mean score, for all events in the data set. We see that there is a very strong positive correlation (near 1) for all the IPA metrics with all the other metrics. And a moderate to strong negative correlation between the mean score and the IPA metrics. The correlation is negative because of the inverse of the relationship between the IPA metrics, which measure errors in various forms and the score. The correlation matrix is displayed in Table 13.

Table 13. Correlation Matrix for IPA Metrics and Mean Score for All Events

	Mean SD X	Mean SD Y	Mean Accuracy	Mean Precision	Mean Score
Mean SD X	1.00	.95	.94	.99	–.75
Mean SD Y	.95	1.00	.92	.98	–.74
Mean Accuracy	.94	.92	1.00	.95	–.62
Mean Precision	.99	.98	.95	1.00	–.72
Mean Score	–.75	–.74	–.62	–.72	1.00

We next examine the possible variability when holding the mean score constant for an event. In this case study we will examine the most common recorded total point values for an event and compare and contrast the information that can be learned about the event by examining the IPA metrics. In the first case, we will examine 143 cases of shooters scoring 49 out of 50 points on Event 4, the 200-yard line rapid fire event. The only possible points combination to receive 49 points on this event is to place all rounds nut one in the 5 area, and one in the 4. The only possible differentiation between shooters would be which of the 10 rounds was the only round that did not strike the 5 area. However, with IPA we can describe a varied range of 6 metrics, which can be used to provide meaningful feedback, to improve shooter performance, and add fidelity to the measurements in the training assessments. Summary statistics are included in Table 14 for the calculated metrics, and visualizations are included in Figures 41 through 43.

Table 14. Range of IPA Vales for Constant Point Score, Event 4

	Min	Mean	Max
Mean X (mm)	–150	11	186
Mean Y (mm)	–170	–40	128
Mean SD X (mm)	51	100	174
Mean SD Y (mm)	49	100	187
Accuracy (mm)	6	96	207
Precision (mm)	77	136	194
Mean Score	4.9	4.9	4.9

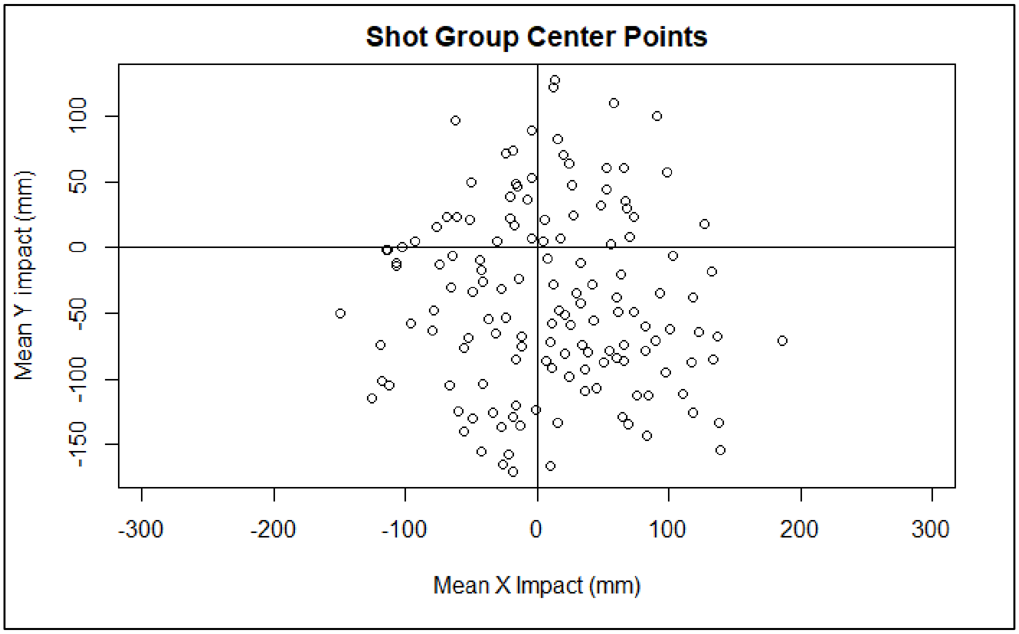


Figure 41. Shot Group Center Points, Constant Point Score, Event 4

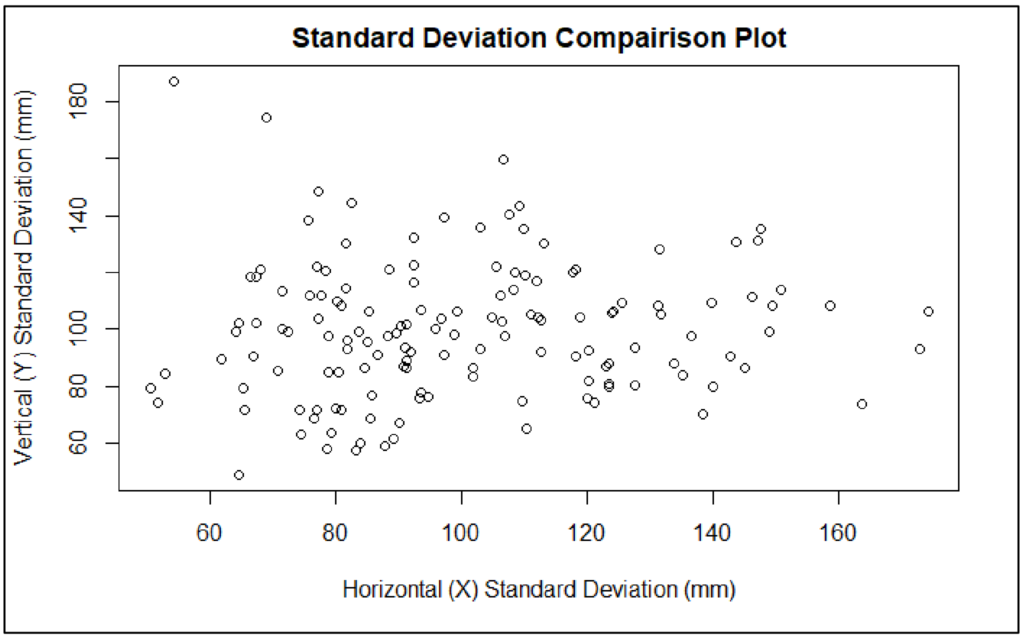


Figure 42. Standard Deviation Comparison Plot, Constant Point Score, Event 4

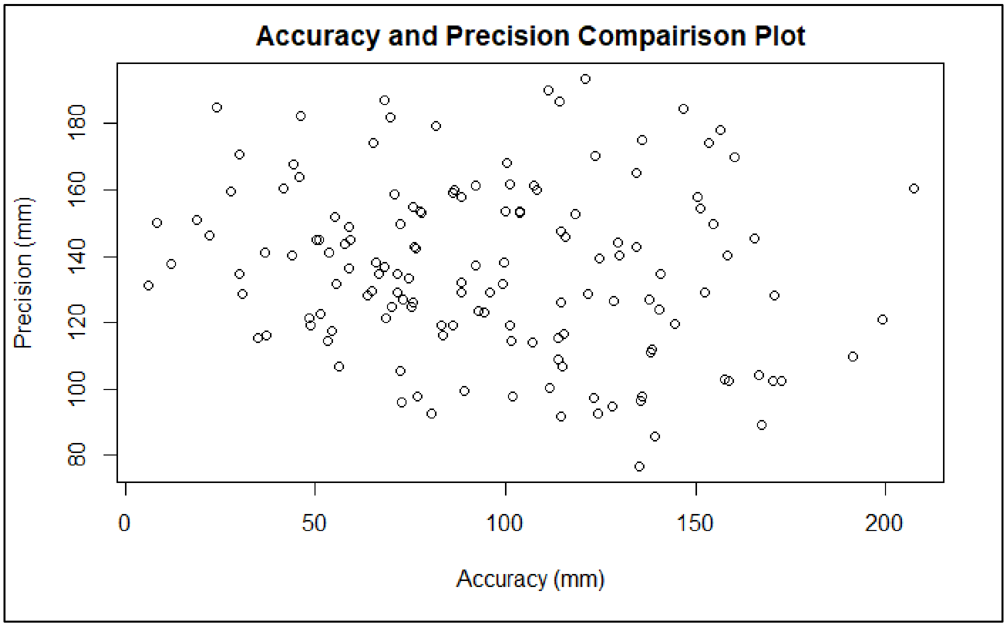


Figure 43. Accuracy and Precision Comparison Plot, Constant Point Score, Event 4

E. ENHANCING THE DATA BOOK WITH ANALYSIS

> The rifle data book is the single most important tool that is available for Marines to evaluate and improve their performance and consistency. The rifle data book is used to record sight adjustments, which enable a zero to be established and maintained. It is critical that all efforts be directed toward establishing a zero setting on the Service rifle that can be taken into combat.
>
> —USMC, 2016

The rifle range data book is a critical tool in the development of marksmanship skills. It is the primary tool that a Marine and his/her coach use to record their progress and performance. The shooter is expected to record the results of each round fired, to include the point of aim, any marksmanship fundamentals errors, and the location of the impact. The result, if properly filled out is a valuable tool for keeping track. (MCRP 8–10B.2, 2016)

As the tool for keeping track of a shooter's performance, it is essential that the Marine Corps makes every effort to make the record as precise as possible. It is critical if the data book is going to be used for making decisions on training that it be an accurate and unbiased record. The current system of self-reporting often produces a biased estimate that varies by shooter and at best is an approximation of true performance.

1. Digital Data Book Development

The concept of a "digital data book" proposed by Wheeler (2019) is expanded in this thesis to include statistical analysis, and a comparison to benchmarks for performance across the events. Our proposed digital data book is created with a script which conducts analysis on the single shooter data frame. The results of the visualizations and analysis are a digital data book with an accurate record of performance and analysis by event. The conceptual framework is displayed in Figure 44.

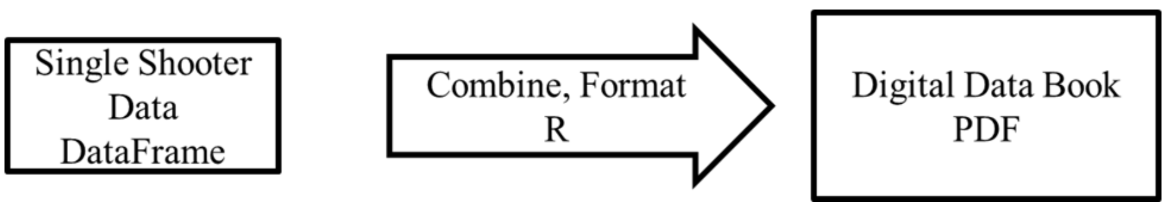
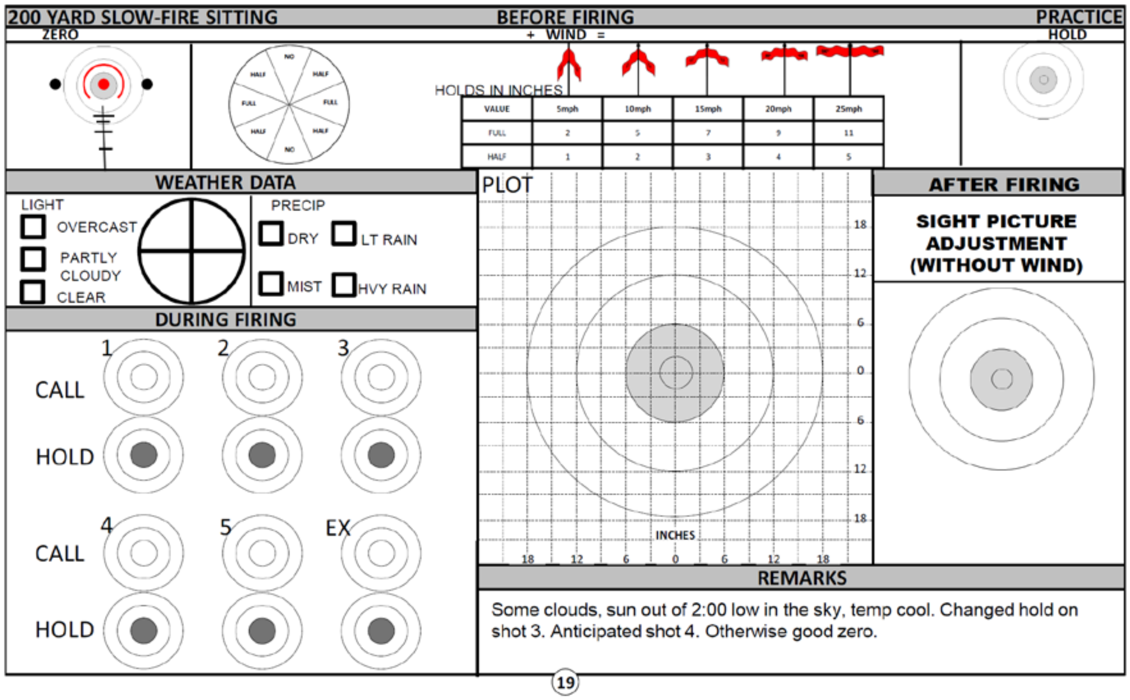


Figure 44. Digital Data Book Development Process

We will begin by showing an example page of the current data book, which is displayed in Figure 45. This page is the record for the 200-yard line, slow-fire sitting event. On the left side of the page, the shooters fill out the "hold" they used, or where they aimed the weapon for each round, and a "call," which is where they expected the round to land after shooting. By recording the difference in the hold and the call, as well as the impact of the round on the large plot in the center of the page, Marines can build their intuition for where to hold to achieve their desired results.



VALUE	5mph	10mph	15mph	20mph	25mph
FULL	2	5	7	9	11
HALF	1	2	3	4	5

Figure 45. 200 Yard Slow-Fire Sitting Data Book Page.
Source: USMC (2019).

2. Data-Enabled Coaching Example

In this section, we will provide an example for a tool which can easily provide a visual display of information to the shooter and the coach more effectively than with the current analog data book. We will use individual shots as well as the mean impact point for each event to identify trends in the shooter's shot group center points to identify any bias in the impacts on the targets.

The data collected from the LOMAH system does not have the ability to capture the hold or the call from the shooter for each round, but it does allow for more precise plotting of the impact than is possible "by eye" as the shooter records their rounds with pen or pencil on the paper data book from 200–500 yards away. By conducting IPA on the shot groups for each event, we have identified the center for each of the 27 events. A graphical depiction of the center points for each shot group for a sample shooter color-coded by the training day is displayed in Figure 46.

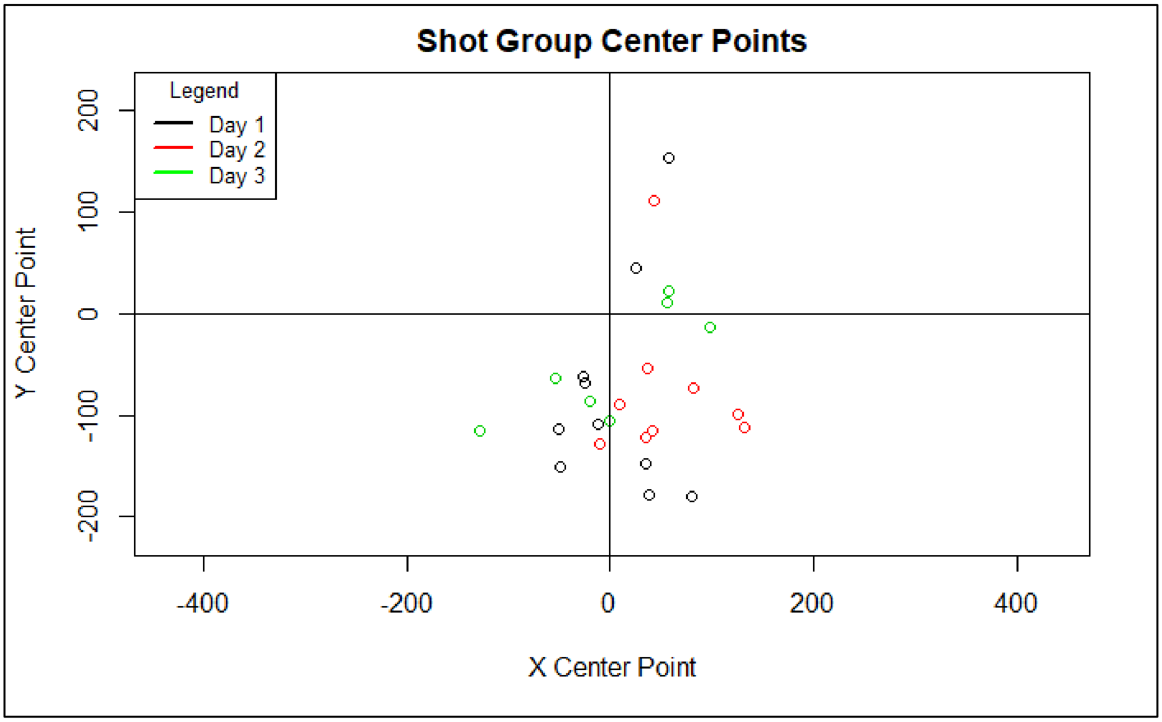


Figure 46. Shot Group Center Points for 27 Events, Sample Shooter

For the analysis is on the center of the shot groups, we consider the location of the center of the shot group with relation to the horizontal and vertical axis. Significant deviations from center in a single event are easy to see when the event is viewed individually. By viewing all the shot group center points on one plot, we can see if the shooters display any general bias in their impacts. This plot shows that the shooter tends to impact below the center of the target on the vertical axis, and to the right of the center on the horizontal axis. As a basic, nonparametric assessment, we can display the count of how many of the observations land on each side of each of the centerlines by counting the sign of the coordinate of the impacts.

Table 15. Locations of Shot Group Center Points

	Left	Right	Total
Above	0	5	5
Below	10	12	22
Total	10	17	

If the data were centered on the center of the target, we would expect 50% of the data to fall on each side of each axis, with approximately 25% of the observations landing in each quadrant on the Table. To test if the data is centered on the center of the target, we conduct two separate binomial tests, one for each axis. In the test, the null hypothesis is that the probability that a center point falls on either side of the axis is .5 and the alternative hypothesis is the probability is not equal to .5. The result of the binomial test is a p-value which is interpreted as the probability that we would see the results as extreme or more extreme than that observed if the null hypothesis is true. We will use a significance level of .05 to interpret the results.

In the vertical (Y) axis, we see that 22 of the 27 events are below the centerline. The probability of this occurring based on the binomial test is examined using the p-value, which in this case equals 0.002, or two in one thousand times we would see such a result if the data were balanced vertically. At a .05 significance level, we reject the null hypothesis and conclude that the shooter has a bias towards low impacts in the vertical axis. This type of analysis can be automated and used to give feedback to the shooter and advise the coach more objectively and perhaps more quickly than the methods currently employed.

In the horizontal (X) axis, however, we find 17 impacts to the right of center. The probability of this occurring based on the binomial test is examined using the p-value, which in this case equals 0.24. That is about one out of four times an unbiased shooter completes the Table 1A course of fire we would expect to see data this extreme or more extreme. At a .05 significance level, we fail to reject the null hypothesis and conclude the shooter does not have bias in the horizontal axis.

Although we set our confidence level at 95% for this analysis, SMEs should be consulted to identify the right level to set the trigger and recommend a change in shooting behavior. A lower confidence level, depending on the feedback from the coach, may be appropriate to start to make adjustments. We can use the patterns of the impacts to identify to the shooter and their coach that a bias exists; however, we cannot determine the cause of the bias. It may be an error in the shooter’s form or body position, or there may be an error with the weapon’s alignment with the Rifle Combat Optic (RCO). We can identify the bias in the data, but it is up to the shooter and the marksmanship coach to identify its cause and the best solution to the issue.

V. CONCLUSIONS AND RECOMMENDATIONS

> All of our investments in data science, machine learning, and artificial intelligence are designed to unleash the incredible talent of the individual Marine.
>
> — General David H. Berger USMC, 2019

A. CONCLUSION

This thesis demonstrates that data collected during the conduct of routine training can be used to conduct analysis and produce results similar to that during large-scale controlled studies. Additionally, collecting data electronically and automatically, the Marine Corps can provide better feedback to their shooters, drawing on automatic calculations to identify trends in the data that is not easily identifiable with current techniques. These methods can be incorporated to directly relate the performance on live fire ranges to the measurement of lethality as developed in the *Lethality CBA* (2018).

We used the first six steps in Kozyrkov's *12 Steps to Applied AI*, as a guide to conduct the analysis and structure our recommendations. All of the analysis conducted can be programmed to be run automatically and generate reports for either individual shooters or subsets of shooters. By establishing a formal plan for electronically collecting range data, implementing data analytics, statistical ML, and AI, the Marine Corps can modernize marksmanship training, provide enhanced tools for coaches and shooters, and directly match assessment feedback to the desired lethality metrics. These improvements can support the CMC's directive to "unleash the talent of the individual Marine" (Berger, 2019) and make the whole Marine Corps a more lethal fighting force.

1. Centralized Analysis

Wheeler 2019 recommended the establishment of the CELIM, a centralized organization to focus on marksmanship excellence and analysis. Part of the proposed mission of this organization would be to analyze marksmanship data in one centralized location using the tools and techniques discussed in this thesis.

The completion of this thesis in March to May 2020, was impacted by the ongoing global pandemic caused by the Novel Coronavirus – 19 (COVID-19). The Department of Defense implemented a set of travel restrictions, which prevented the author of this thesis from conducting a site survey to the CHRC in Miramar, CA. While this restriction was initially viewed as a limitation, we took it as an opportunity to demonstrate the capabilities of centralized analysis. The only data used in this thesis was transmitted digitally through file sharing, and all the coordination was conducted remotely. The author has experience participating in the Marine Corps marksmanship training programs; however, we do not have near the level of experience as the authors of the studies on which this research is based. This demonstrates that a properly trained analyst, can be effective at modeling marksmanship performance and gathering insights that can be used to make informed decisions about training.

Both the individual and the aggregate analysis conducted in this thesis are scripted in the R programming language and are programmed with the flexibility to add more data, or to be repeated on any induvial shooter. This makes the analysis repeatable and can be run routinely on each new data set as it is created. This demonstrates the repeatability of the effort and applicability to incorporation into a process that could be managed by the CELIM.

2. Impact Pattern Analysis

By conducting impact pattern analysis, and calculating the accuracy, precision, and standard deviation for each event, we gather more information about each event and each shooter. This additional information can be used to compare events across ranges and target silhouettes with more fidelity than a point-based scoring system.

We have demonstrated the capabilities of information age data analysis, data visualization, and machine learning to provide feedback to shooters and coaches in a meaningful way that is likely to aid in marksmanship training in a manner far superior to current industrial age methods. The identified metrics provide a framework to measure the performance of a shooter in a way far superior to discrete point values.

3. More Accurate Probability of Hit Calculations

By close verification of assumptions used in previous analysis on the dataset we are analyzing, we were able to identify a departure from normality of impacts in both the horizontal and vertical axis for all events. We identified a discrepancy in the P_{HIT} calculations through simulation if the data is generated using a normal distribution. We developed and tested an alternative method for calculating the P_{HIT} using bootstrapping and these calculations were within 1% of the observed percentages for all events.

4. Improvements with Training

We have explored methods for measuring the improvements in marksmanship with training. We first examined the decrease in horizontal and vertical standard deviations for the combinations of range and target type across the three days of training. This confirmed the presence of a trend in the data for groups of shooters when evaluated as a whole.

We were able to construct a framework to test both individual shooters and shooters as a whole. By properly subsetting and comparing the data, we can analyze if a shooter is improving in accuracy, precision, or both across the three days of training. These calculations can be particularly useful for a shooter who is struggling with one skill set or another. By identifying analytically what the shooter needs to work on, the coach can work on specific drills to address the deficiencies.

B. RECOMMENDATIONS

Based on the conclusions drawn in this thesis, we make the following additional specific recommendations. These recommendations are based on, expand on, and are in agreeance with the recommendations by the Lethality CBA and by Wheeler in AETLEM. The first three recommendations are procurement related, and the last is structure related. By implementing these recommendations, the Marine Corps will lay the foundation for leveraging the data available to enhance the lethality of the individual Marine, assess future weapons, and target training.

1. Implement LOMAH Sensors at all Live Fire Marine Corps Ranges

The analysis conducted in this thesis can only be conducted if LOMAH data is available. Prior to this thesis and Wheeler (2019), analysis was only conducted on LOMAH data as part of a deliberate experiment. This greatly limits the data available, and as weapons, equipment, and tactics change and evolve, the data quickly becomes obsolete.

We recommend establishing a priority to fund and install KDAS systems at ranges where marksmanship training is conducted, as this will build a larger data set quickly to model how Marines learn and develop marksmanship training skills from the beginning. Establishing a record for each new Marine as they begin their journey in learning marksmanship will lay the foundation to track their performance analytically from one training event to another.

Additionally, as demonstrated in this thesis, the Table 1A, KD range is structured in a manner that allows for the assessment of the same skill set under similar conditions over time. By measuring the Marine's performance on each training evolution in the same method over their career, the feedback calculated in the digital data book will guide the shooter and the marksmanship coach.

Much in the same way we were able to map performance from the first day of training to the third day, with a larger data set, we can map how shooters perform from one year to the next or from one course of fire to another. This larger data set can also be used to determine the effects of new equipment and training, perhaps even overall Marine Corps lethality.

2. Require Network Conductivity for LOMAH Systems

The data generated by LOMAH systems are not being used to their full potential if they are not able to be linked to an individual, used to provide feedback in the form of training assessments, and transmitted for analysis and storage. The LOMAH systems at each range therefore must be connected to the Marine Corps network infrastructure. The Marine Corps has stringent requirements for all systems connected to the network, and these requirements are nontrivial to be met and maintained. Therefore, we recommend that this capability be included in the requirement and funded during the acquisitions process.

Data for each event should be validated at the range by the range operators, and only capture data from performances by Marines on the range that is free from equipment errors in either the weapon system or the sensor suite. At the end of the training evolution, the data will be certified by the range personnel, and transmitted to the CELIM. By establishing a single procedure for transmitting the data which is required for the Marine's performance to be counted, the desired impact placement data will automatically be transmitted along with the score data.

C. RECOMMENDED FUTURE WORK

1. Weather Data

The variations present in the impact patterns of rounds on the target are affected by the shooter's application of the marksmanship fundamentals, the inaccuracies inherent in the weapon system, and the effect of the weather on the round as it travels from the shooter to the target. By collecting weather data at the rifle range during the conduct of training future research could separate some of the weather effects from the effects of the shooter. This will allow for a normalized data set and make the data from one day to another more comparable.

The weather data can further refine the analysis conducted on the individual shooters as well. Range conditions may explain the variability in the round impacts that are present in the data, but otherwise go unexplained. For example, if wind increases as the day goes on, this might explain an increase in variability for later relays in the day. Additionally, the currently used hard copy data book has space for Marines to manually record weather conditions. By recording the weather automatically and electronically, we can remove the requirement for the shooter to physically capture the weather data, compare the true values to those recorded by the shooter and evaluate the accuracy of the shooter's estimates of the weather recorded. These estimates can then be compared with the shooter's call and hold and the recorded impacts.

By conducting IPA on data with associated weather data, we can better model the effects of weather on the accuracy and precision of shooters. This knowledge can then help the Marine Corps make decisions about marksmanship training surrounding weather. For example, windspeeds over a certain threshold may be identified as having no training value, true impacts of mist or rain on shots may be ascertained, and more effective recommendations concerning training conditions can be made.

2. Predictive Modeling with Detailed Information from Shooters

Gather data from the shooters participating on a range detail at CHRC and repeat a similar analysis to that conducted in *Predictive Models of User Performance for Marksmanship Training* (2018). With the appropriate permissions, retrieve personally identifiable information for each Marine already available in personnel records, and data on the weapon they are training with. Gather information available in USMC personnel records, and after the completion of the training event, compile the results from the training with the Marine's survey results and training history. Use the data to determine what factors may have a predictive ability to provide insight into marksmanship training. Any information that can be useful in predicting performance can be included in the models to make more efficient and effective use of training time and resources.

3. New Course of Fire

As this thesis is being written, the Marine Corps is developing a new course of fire designed around the findings of the *Lethality CBA* (2018) which was addressed in Wheeler (2019) but was outside the scope of this thesis. In the new course of fire, which will be called the Annual Rifle Qualification, a new target silhouette will be used. The silhouette is based on the lethal areas as described in Chapter II. The new Threat Target, as it is called, has three separate areas that serve as the target center, depending on the event. The target is called the USMC Threat Target, and it is a man-shaped silhouette with target areas on the lethal areas defined in Chapter II. If LOMAH data can be obtained for the new course of fire, repeating this analysis on the new course of fire data will be beneficial to demonstrate the capabilities and flexibility of IPA on the new course of fire.

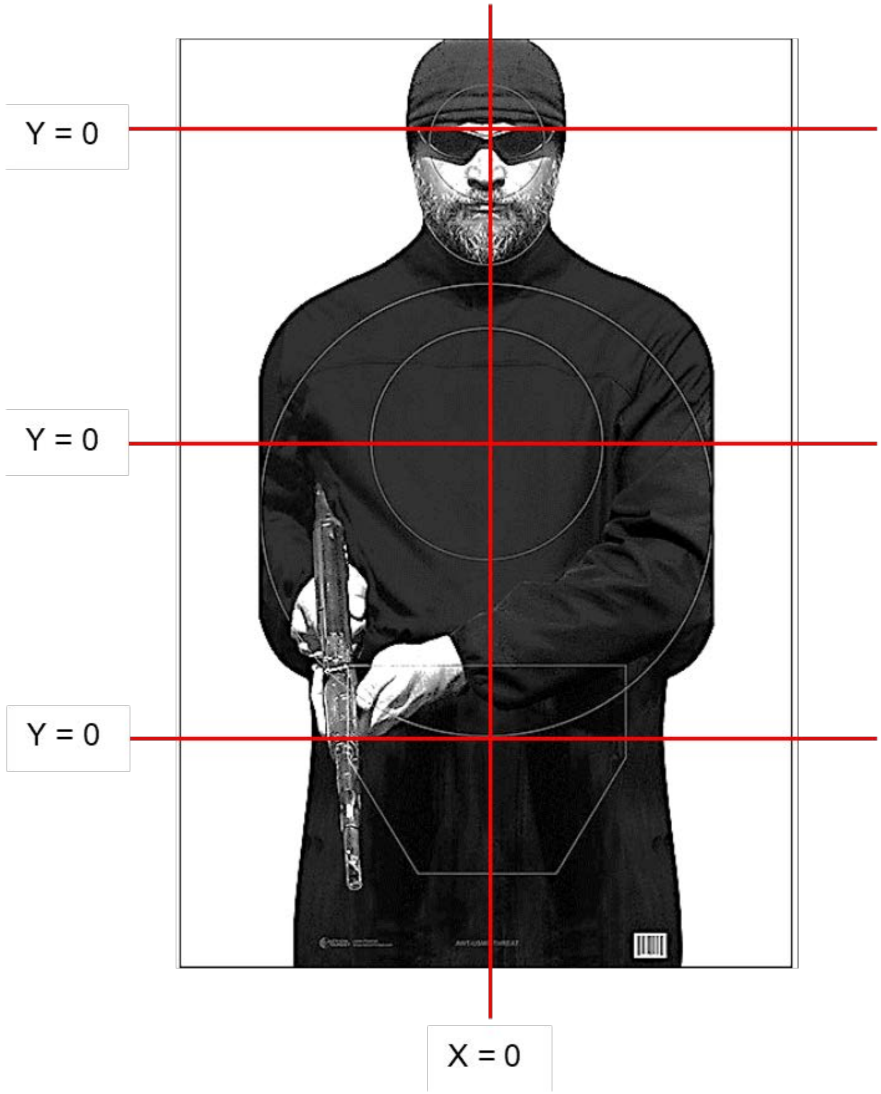


Figure 47. Three Coordinate Systems on USMC Threat Target. Adapted from Wheeler (2019).

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